# Essays in Corporate and Consumer Finance

A DISSERTATION PRESENTED

BY

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TO

THE DEPARTMENT OF BUSINESS ECONOMICS

IN PARTIAL FULFILLMENT OF THE REQUIREMENTS
FOR THE DEGREE OF
DOCTOR OF PHILOSOPHY
IN THE SUBJECT OF
BUSINESS ECONOMICS

HARVARD UNIVERSITY
CAMBRIDGE, MASSACHUSETTS

MAY 2013

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## Abstract

The first essay tests whether Chapter 11 restructuring outcomes are affected by time constraints in busy bankruptcy courts. Using the passage of the Bankruptcy Abuse Prevention and Consumer Protection Act in 2005 as an exogenous shock to court caseloads, I estimate the impact of bankruptcy caseload changes on the outcomes of firms in Chapter 11. I find that as bankruptcy judges become busier they tend to allow more firms to reorganize. Firms that reorganize in busy courts spend longer in bankruptcy, while firms that are dismissed from busy courts are more likely to re-file for bankruptcy within three years of their original filing. In addition, busy courts impose costs on local banks, which report higher charge-offs on business lending when caseload increases.

Using novel data that has complete coverage of claims for 136 Chapter 11 bankruptcy protection filings and that includes detailed information on claims transfers, in the second essay we provide the first empirical insight on how a firm's ownership changes during the bankruptcy process and how these changes impact bankruptcy outcomes. Pre-bankruptcy ownership concentration is important for the coordination of a prearranged bankruptcy filing and is associated with a faster bankruptcy resolution and a higher likelihood of a successful reorganization. However, as the trading of claims *in* bankruptcy concentrates ownership further, the probability of liquidation increases and recovery rates decrease.

The third essay studies whether prize-linked savings (PLS) accounts, which offer random, lottery-like payouts to account holders in lieu of risk-free interest, can aid individuals in increasing savings levels by adding the chance to "win big." Using micro-level data, we show that PLS is attractive to a broad group of individuals across all age, race, and income levels. We find that financially constrained individuals and those with no other deposit accounts are particularly likely to open a PLS account. Participants in the PLS program increased their total savings on average by 1.1% of annual income, a 31% increase from the mean level of savings. Deposits in PLS do not cannibalize savings in standard savings products. Instead, PLS appears to act as a substitute for lottery gambling.

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# ACKNOWLEDGMENTS

Writing a dissertation can feel like a solitary experience, but when the time comes to put all of the pieces together it is overwhelming to realize just how much support I have had while doing this work. I was blessed to have passed through this experience with incredible advisers, collaborators, friends, and family members to provide encouragement, new ideas, and criticisms that have made these essays far better than I could have made them by myself.

First, I would like to thank the chair of my dissertation committee, co-author, and friend, Victoria Ivashina, for teaching me how to work through the research process and for providing invaluable support and advice especially during the final year of the program. I absolutely could not have done this without her. I also thank my other advisers, Jeremy Stein, David Scharfstein, and Stuart Gilson, for their encouragement and willingness to dedicate hours of their time to give me feedback and advice as I worked toward completion of the Ph.D. In addition, I owe special thanks to my co-authors Shawn Cole, Peter Tufano, and especially David Smith for their help in preparing the second and third essays in this dissertation.

In addition, this research has benefitted from comments from a host of other individuals, including Bo Becker, Shai Bernstein, Jonathan Carson, Lauren Cohen, Judge Joan Feeney, Robin Greenwood, Sam Hanson, Howell Jackson, Chris Malloy, Bill Norton, Mark Roe, Judge Geraldine Mund, Andrei Shleifer, Per Strömberg, and Adi Sunderam. I'm thankful to all of them for their help and advice.

But mostly, I owe everything to my incredible family. First, to my parents, Ned and Linda, who taught me to plan, work and take pleasure in a job well done, and who have provided undying love for 31 years and counting. Second, to my boys, Henry, Ellis, and Sam, who provided balance and perspective and laughter when I most needed it, and who are examples to me of never-ending curiosity. And finally, to my dazzling wife Jenn, who has taken every step of this journey with stamina, encouragement, patience, humor, and love. She means everything to me.

# 1

# Get in Line: Chapter 11 Restructuring in Crowded Bankruptcy Courts

## 1.1. Introduction

The purpose of Chapter 11 bankruptcy is to protect the assets of financially distressed firms from seizure by creditors while the restructuring options available to the firm can be considered. As pointed out by Hart (2000), one of the main goals of an efficient bankruptcy procedure is to reorganize distressed firms only when their value as a going concern exceeds their liquidation value. Bankruptcy, then, has an important impact on the allocation of capital in an economy, as it acts as a filter that separates distressed firms that are still economically viable from those whose assets should be redeployed via liquidation. Prior research, reviewed below, has focused on how the design of bankruptcy procedures might affect the allocation of capital by altering the outcome of the case or causing frictions that diminish the overall value of the distressed firm. This essay builds on these previous studies by showing that the efficiency of the court itself (not just the laws that govern the court) has an important impact on the costs of financial distress and on the ultimate outcome of the bankruptcy.

In particular, I focus on the total caseload that bankruptcy judges must deal with. Judge workload fluctuates widely as economic conditions change. For example, total bankruptcy filings rise nationwide on average by 32% during economic recessions. Large differences in workload are also common cross-sectionally, as local economic deteriorations lead to increasing caseload for judges in those areas.[1] Because total judge workload is counter-cyclical, judges are busiest exactly when financial distress is worst. As Judge David S. Kennedy stated, "Actually, there are times and days when I feel like the bankruptcy court today is more a de facto emergency room for financially distressed consumer and commercial debtors…as judges, I note that sometimes we can just get too busy." (Bankruptcy Judgeship Needs, 2009)[2]

The bankruptcy judge plays an integral role in Chapter 11 restructuring. As Gilson (1999) states, "the Bankruptcy Code effectively requires judges to set corporate operating policies…judges have broad powers to influence how the firm's assets are managed." The bankruptcy judge is ultimately responsible for determining whether a debtor firm should be liquidated or reorganized, and for ensuring that reorganized firms have a reasonable chance at avoiding financial distress in the future. A large body of research has focused on whether judges tend to be more friendly towards debtors or creditors during this process (Chang & Schoar, 2007; Hotchkiss, 1995; LoPucki, 1983; Morrison, 2005). Judges who allow the continuation of the firm are typically viewed as pro-debtor, as continuation can benefit equity holders who prefer riskier outcomes due to limited liability (Jensen & Meckling, 1976) or provide private benefits to the debtor's management (Aghion, Hart, & Moore, 1992). Failing to liquidate non-viable firms harms creditors, who do not participate in the upside potential of the firm and may even receive higher recovery rates under liquidation, depending on the ability to redeploy the assets of the firm (Benmelech &

[1] For example, the collapse in house prices in 2007 and 2008 hit Arizona much more severely than Texas. As a result, in 2009 there were 5,000 bankruptcy filings per judge in Arizona, as compared to roughly half as many cases per judge in Texas.
[2] Legal researchers have long been concerned about the effect of heavy caseloads on federal judges' decision-making. See, for example, Friendly (1973) and Ginsburg (1983).

Bergman, 2009). In this chapter, I examine variations in time constraints that judges face and test whether busy judges are more or less likely to allow firms to emerge from Chapter 11.

It is natural to expect that time constraints will affect judge decision-making. A time-pressured judge will find it costly to gather and consider information about each case, thereby increasing the risk of errors in judgment. Given this, a busy judge may be reluctant to liquidate a distressed firm, preferring instead to allow the firm to reorganize and preserving the option to liquidate the firm at a future date.[3] In addition, psychological research shows that when individuals are stressed or fatigued they are unable to think through complex problems, and hence tend to "kick the can down the road" by putting off final decisions or deferring to others whenever possible (Huang, 2011; Karau & Kelly, 1992; Pocheptsova, Amir, Dhar, & Baumeister, 2009). Individuals with strict time constraints tend to focus only on finding a quick solution to the task at hand, often exhibiting less scrutiny of the merits of that solution and ignoring other important issues that seem less pressing, even when this behavior is quite costly to the individual (Kahneman, 2011; Perlow, 1999; Shah, Mullainathan, & Shafir, 2012). Applying this logic to bankruptcy, a time-pressured bankruptcy judge will likely be reluctant to make the final decision of liquidating a marginal firm, and will instead defer to the debtor's management since by default the debtor retains control of the firm after filing (Franks, Nyborg, & Torous, 1996).[4]

To empirically test the impact of busy courts on financially distressed firms, I use a natural experiment that exogenously impacted the caseload of bankruptcy courts. In 2005, Congress passed the Bankruptcy Abuse Protection and Consumer Protection Act (BAPCPA), which made it substantially more difficult for households to file for bankruptcy protection. After the October 17th, 2005 deadline imposed by BAPCPA, non-business bankruptcy filings dropped dramatically, and stayed at extremely low levels

[3] This would be the case if the judge's preferences are such that he prefers continuation of an unviable firm (a type I error) to liquidation of a viable firm (a type II error).

[4] An alternative hypothesis is that busy judges might seek to do whatever necessary to clear their dockets as quickly as possible. Because liquidations and dismissals take less court time than reorganizations, under this hypothesis it would be expected that busy judges would liquidate and dismiss more cases and reorganize fewer cases. Cross-sectionally, this hypothesis would also predict that busy judges would seek particularly to liquidate the largest and most complex firms, as these are the most costly for overburdened judges to deal with. The empirical evidence presented in Section 1.5 is exactly contrary to this idea, suggesting that judges' reactions to heavy caseloads are more nuanced.

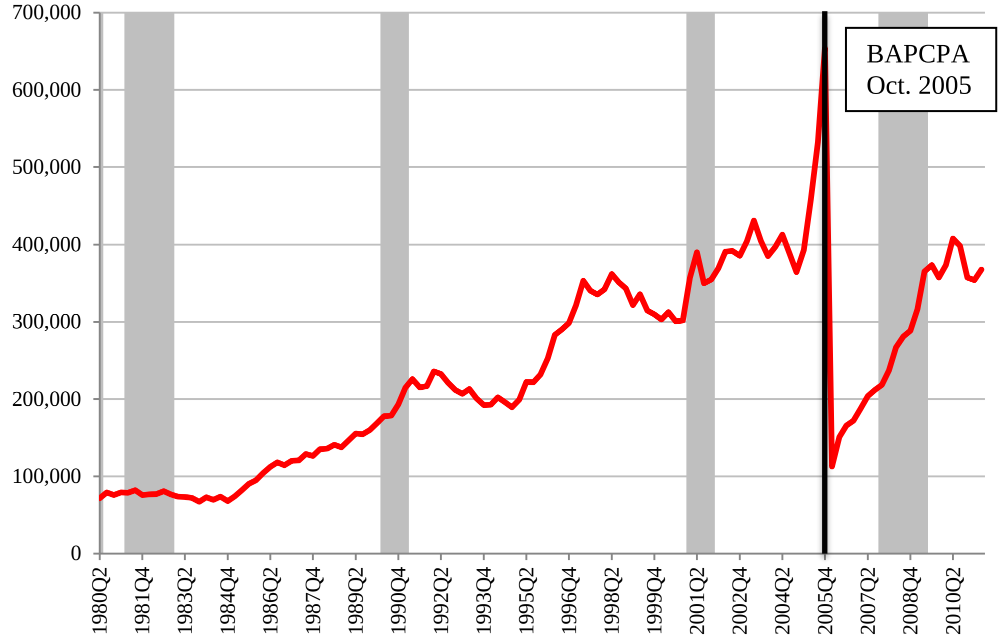
until the onset of the financial crisis (Figure 1.1, Panel A). Since bankruptcy judges rule on *both* business and non-business cases (i.e., there is no specialization among bankruptcy judges), BAPCPA created a large shock to the workload of bankruptcy judges across the nation, cutting average caseloads in half. BAPCPA did not impact all districts equally, however. In particular, courts that handled a relatively higher share of personal bankruptcy cases saw caseloads drop by larger amounts after BAPCPA took effect. For example, prior to BAPCPA, a judge in the District of Oregon spent about 78% of her time on non-business bankruptcy cases, and BAPCPA reduced her caseload by 62%. Just south of Oregon, in the Northern District of California, judges spent about 71% of their time on non-business cases, and the corresponding drop in caseload was only 39%. Using difference-in-differences specifications, I exploit this exogenous variation to estimate the *causal* effect of total judge caseload on a variety of firm outcomes.

Using information on 3,327 Chapter 11 bankruptcies filed between 2004 and 2007, I find evidence that busy bankruptcy judges that were exogenously busier due to BAPCPA are more likely to allow debtor firms to restructure and emerge from bankruptcy, rather than being liquidated via conversion of the case to Chapter 7 or dismissed from court altogether. This is especially true for larger, more complex firms, which would be most likely to tax already overburdened judges. As a result, bankrupt companies that might have been liquidated in a less-busy court are allowed to reorganize and emerge from bankruptcy. This suggests that as judges become busier, they become more pro-debtor as well.

To understand the impact of this shift in bankruptcy outcomes, I test whether firms which exit bankruptcy in busy courts are able to avoid financial distress in the future. Following previous literature[5], I use the recidivism rate – the probability that a firm re-enters bankruptcy within 3 years of its original

[5] Chang & Schoar (2007) state that "re-filing, even more than firm dissolution, can be seen as the ultimate failure of the bankruptcy process." Gilson (1997) and Hotchkiss (1995) use recidivism as a measure of inefficient restructuring as well. Recidivism is also commonly used to assess the efficiency of mortgage loan modifications (see, for example, TransUnion, 2012).

*Panel A: Non-business case filings (number of filings)*




*Panel B: Business Chapter 11 case filings*

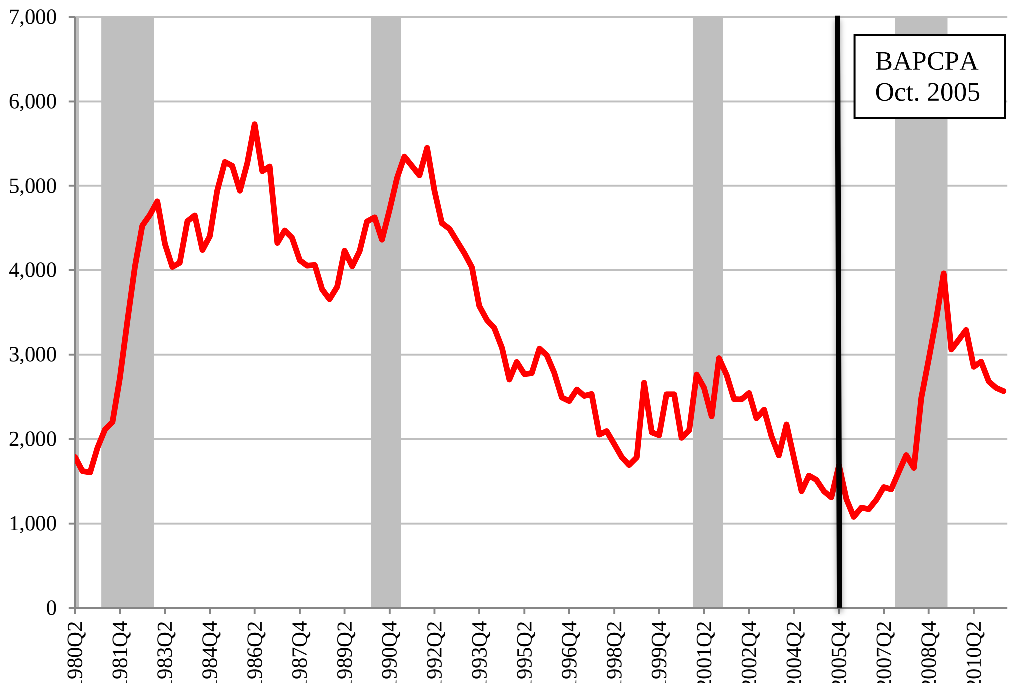



**FIGURE 1.1 - BANKRUPTCY CASES FILED PER QUARTER – NON-BUSINESS AND CH. 11**

Panel A shows the total number of non-business bankruptcy filings per quarter in the U.S. Courts system from 1980Q2 – 2011Q2, while Panel B shows the total number of Business Chapter 11 cases filed. In both charts, the vertical line identifies the passage of BAPCPA in October 2005, while light-gray shading indicates NBER recessions.

filing – as an indicator of firms which exit bankruptcy but remain fragile or distressed.[6] I find that firms which successfully reorganize in busy bankruptcy courts are no more likely to re-file for bankruptcy than firms that reorganize is less busy courts. However, firms which are dismissed from busy courts have substantially higher recidivism rates, suggesting that either these dismissed firms are more willing to re-file in busy courts in hopes of obtaining a more favorable outcome the second time, or that the causes for dismissal in busy courts are less sound. Regardless of the reason, recidivism almost surely raises the costs of financial distress for these firms as they are not rehabilitated or liquidated the first time through court.

Because the equity value of the bankrupt firm is negative or close to zero, additional costs of financial distress must be principally borne by the creditors of the firm. Using regulatory data reported by commercial banks, I indirectly measure the default costs passed on to creditors by examining the net charge-off rate of commercial and industrial (C&I) loans reported by banks that were particularly exposed to the BAPCPA caseload shock. Because local banks are the predominant source of funding for small businesses (Petersen & Rajan, 1994), they should bear the brunt of higher bankruptcy costs when these firms default. Consistent with this intuition, I find that banks that are located in exogenously busier bankruptcy districts report higher C&I loan charge-off rates.

The economic impact of judge caseload is large. Using the estimates from the BAPCPA natural experiment as guide, I estimate that a 32% rise in filings (the average rise during economic recessions) increases the probability that a bankrupt firm will be reorganized by 8.2 percentage points, a 27% increase from the unconditional probability of 30%. This same shock to bankruptcy caseloads more than doubles the recidivism rate among firms that are dismissed from court after their first filing, and increases the net charge-off rate on C&I loans by 24 basis points, a 47% rise relative to the mean rate of 51 basis points.

[6] A firm might be unviable for one of two reasons. First, it might be *economically* unviable if, regardless of its capital structure, it cannot be profitable. Second, it could be *financially* unviable if it exits bankruptcy with elevated leverage, leaving it overly exposed to temporary shocks going forward.

In addition to these main findings, I find that crowded bankruptcy courts impose other costs on financially distressed firms, including increased time spent in bankruptcy. As one might expect, bankruptcy stays – the length of time between the filing and resolution of the case – are longer in busy courts, particularly for firms that eventually reorganize. I estimate that a 32% increase in court workload lengthens the stay in bankruptcy by six months for a reorganizing debtor. Longer stays in bankruptcy require debtor firms to have more cash on hand in order to continue operations while in court. As a result, I find that smaller firms, which have less access to outside capital, are more likely to sell assets in order to raise cash.

These results are robust to a battery of checks that verify that the estimates are not driven by alternative channels, i.e. the exclusion restriction is satisfied. In particular, controlling for differential effects over time by industry, size, or geographic region does not affect the results. I also confirm that the results are not affected by sample composition effects by using a matched sample before and after BAPCPA. In all cases the impact of caseload on bankruptcy outcomes remains largely unchanged.

Taken together, my results show that overall costs of financial distress are higher in busy bankruptcy courts, and that busy bankruptcy judges make different decisions regarding the allocation of assets of bankrupt firms by liquidating fewer firms. These findings relate to a large literature on the costs of financial distress (Andrade & Kaplan, 1998; Bris, Welch, & Zhu, 2006; Elkamhi, Parsons, & Ericsson, 2012; Warner, 1977) as well as investigations into the design of bankruptcy systems and their impact on debt contracts (Aghion et al., 1992; Bolton & Scharfstein, 1996; Gennaioli & Rossi, 2010; Gertner & Scharfstein, 1991; Strömberg, 2000). In addition, this essay also broadly relates to the literature on complexity costs and bounded rationality (Cohen & Lou, 2012; Hirshleifer & Teoh, 2003; Hong & Stein, 1999). In this vein, research that examines job performance and decision-making under time constraints is particularly relevant to my research.[7] Fich & Shivdasani (2006) show that busy boards are associated with weak corporate governance. Coviello, Ichino, & Persico (2010) show that judges who juggle too

[7] See (Jex, 1998) for an overview of the psychological research in this area.

many cases at once have worse job performance. Huang (2011), using an empirical methodology similar to mine, finds that busy appellate court judges exhibit lightened scrutiny over district court decisions.

The rest of the chapter proceeds as follows. Section 1.2 gives more background about the role of the judge in Chapter 11 bankruptcy and measures of judge caseload. Section 1.3 describes the impact of BAPCPA on court caseload and develops my empirical strategy. Section 1.4 describes the data in my sample. Section 1.5 analyses the impact of caseload shocks on restructuring firms. Section 1.6 concludes.

## 1.2. Bankruptcy process

### *1.2.1. The role of the bankruptcy judge*

When a corporation files for Chapter 11 bankruptcy protection, it is randomly assigned to one of the bankruptcy judges in the district in which it files.[8] From the first-day motions until the end of the bankruptcy case, the judge's main role is to review motions that are brought before the court and to determine whether to grant those motions. Typically, each motion is accompanied with a brief which lays out the argument for granting the petition. It is estimated that bankruptcy judges on average read well over 100 pages of legal briefs a day, and at least one judge admits that "eye fatigue and irritability set in well before page 50" (Keane, 2010). After reviewing the motion, a hearing is held in which oral arguments can also be presented on either side, and the judge will make a ruling either immediately (so-called "ruling from the bench") or in writing afterwards.

Among the most important motions brought before the judge are petitions to dismiss a bankruptcy case or convert it to Chapter 7 liquidation. While conversion to Chapter 7 almost certainly means the death of the firm, motions for dismissal are less clear. Dismissal from court essentially means that the

[8] Debtors can file for bankruptcy in any court containing the debtor's "domicile, residence, principal place of business…or principal assets in the United States." The debtor may also file in a court "in which there is a pending case…containing such person's affiliate, general partner, or partnership." (28 USC § 1408) In the case of corporations, this is typically interpreted to mean that a firm can file either (1) where they are incorporated, (2) where they are headquartered, or (3) where they do the bulk of their business. This gives the largest, nationwide firms substantial leeway in the choice of bankruptcy venue, but for most corporations these three locations are one and the same and therefore they are not able to "shop" for a more suitable bankruptcy venue. In my sample, 295 firms (8.9%) filed in bankruptcy districts different from the address they reported on their petitions. Excluding these firms from the sample does not change any of my conclusions.

firm remains as if no bankruptcy had ever been filed. Negotiations can continue between debtors and creditors, but creditors are given power to seize assets or seek legal action against the debtor. Dismissed firms can re-file for bankruptcy, but will typically have to show that they are in need of bankruptcy protection and have potential to be successfully rehabilitated; otherwise, the case will be dismissed again, potentially with legal consequences for a bad-faith filing. Overall, dismissal is a close equivalent to conversion in many cases; the firm is dismissed from court but will still be liquidated because it has not been restructured in any way. Morrison (2005) confirms that most dismissed firms cease operations shortly after exiting bankruptcy.[9] This is particularly true for smaller firms, which have less ability to fight lawsuits in court or negotiate with creditors outside of court.

Because it is the bankruptcy judge who gives the final decision on the motion to dismiss or convert, he acts as an important filter in determining which firms are economically viable and which should be liquidated. Indeed, Morrison (2005) states that, "Neither debtors (managers or equity-holders) nor creditors dominate the bankruptcy process. Instead, bankruptcy judges play a major role in filtering failing firms from viable ones." The judge's ability to correctly determine where capital can most effectively be allocated largely determines the efficiency of the Chapter 11 process itself.

Another key role of the bankruptcy judge is to rule on the feasibility of a Chapter 11 plan of reorganization. Once a Chapter 11 filing has taken place, the debtor has a 120-day exclusivity period within which it has the sole right to file a plan of reorganization.[10] The plan of reorganization outlines how the debt of the firm will be restructured and the creditors of the firm will be repaid. The plan must also estimate the enterprise value of the firm under Chapter 11 continuation, and show that this value is greater than the expected value if the firm were to be liquidated under Chapter 7. With a plan formulated,

[9] In the appendix I provide more detail about why firms are dismissed from court and what happens to them after they leave court.

[10] The debtor can petition the judge to extend this period of time, up to a maximum of 18 months. Once the exclusivity period has expired, a creditor, group of creditors, or a case trustee are allowed to file competing plans. In practice the vast majority of plans are created and filed by the debtor, after negotiating with creditors (Weiss, 1990).

the proponents of the plan create a disclosure statement which, once approved by the judge, is sent out to all creditors so that they can vote on whether to accept it or not.[11]

Even after a plan has been accepted by the creditors, however, the judge has the final say.[12] Specifically, the judge must find that the plan is filed in good faith, gives a superior recovery to creditors than if the firm had been liquidated in Chapter 7, and is feasible. To find that the plan is feasible, the judge must "find that confirmation of the plan is not likely to be followed by liquidation or the need for further financial reorganization" (United States Courts, 2011). In short, the judge must agree that the plan does enough to ensure that the firm will be viable going forward. While this objective is specifically laid out for the judge in the Bankruptcy Code, there are no direct monetary consequences for a judge who allows an unviable firm to reorganize, since in practice it is nearly impossible to determine when this occurs. However, there are reputational concerns for bankruptcy judges.[13] In particular, all of a judge's decisions are part of the public record, and any ruling can be appealed before a higher court.

Aside from direct decisions that determine whether a firm is allowed to reorganize, judges also rule on motions which alter other important aspects of the bankruptcy process. One of the most important of these is the motion to sell assets. The sale of an asset in bankruptcy can ease negotiations between debtors and creditors because it replaces the asset, which creditors typically do not want to own, with cash that creditors are happy to take. Assets sold in these so-called "Section 363" sales (named after the section of the Bankruptcy Code that governs the sales) are sold free and clear of any liens, giving protection to potential buyers from further legal action (Gilson, 2010). However, Pulvino (1999) shows that assets sold in Chapter 11 restructuring are typically sold at deeply discounted prices, indicating that these sales could hurt recovery rates for creditors. Pulvino (1999) argues that in general asset sales benefit the debtor, because the proceeds of the sale bring much-needed cash into the firm, allowing it to

[11] A plan is approved if at least one half in number and two thirds in value of all creditors in each voting class (seniority level) votes in favor of the plan.
[12] In fact, the judge can even force creditors to accept a plan they have voted against in a so-called "cram-down" if she feels that the plan is the best overall options available to the firm.
[13] For example, Weidlich & Kary (2008) reported specifically on Judge James Peck's reputation when he was assigned Lehman Brothers bankruptcy case.

continue operating during bankruptcy or to pay off creditors that the debtor does not want voting on the plan of reorganization.[14] It is up to the judge to determine whether these sales should be allowed to take place and to ensure that the auction process is fair.

Other motions that judges consider include petitions to lift the automatic stay and allow creditors to seize certain assets, to extend the exclusivity period, or to allow the use of cash collateral. Each of these decisions can tip the balance of power between debtors and creditors, indirectly affecting the ability of a firm to successfully reorganize.

*1.2.2.Measuring bankruptcy court caseload*

The number of bankruptcy judgeships in the United States is determined by Congress, and the creation of new judgeships requires the passage of a bill by both the House of Representatives and the Senate. Every other year, the Judicial Conference of the United States conducts a study of the caseload of bankruptcy judges and recommends to Congress the number of new judgeships that are needed for each bankruptcy district. Despite consistent pleas for more judges from the Judicial Conference, the last time Congress approved new permanent judgeships was in 1992.[15] As a result, judge workloads have increased dramatically. From 1980 to 2010, total bankruptcy filings rose by 381% while the total number of bankruptcy judges only increased by 53%. Put differently, the average bankruptcy judge in 2010 handled 3.1 times more cases than the average judge in 1980.

But each bankruptcy case does not demand an equal amount of the judge's time. Personal Chapter 7 cases rarely even go before a judge, while a complex Chapter 11 filing will take many hours of court time. Because of these differences, the Judicial Conference uses a weighting system to calculate the caseload for each bankruptcy district. The weights come from a judge time study conducted in 1989 (Bermant, Lombard, & Wiggins, 1991), and indicate the number of hours a judge spends on each of six types of bankruptcy cases (Table 1.1): non-business Chapter 7, business Chapter 7, Chapter 11, Chapter

[14] Only creditors that are deemed "impaired"—meaning they do not receive 100% recovery—are allowed to vote on the plan. By paying off some creditors with cash proceeds, they can be blocked from voting on the plan.
[15] In 2005, 28 new temporary judgeships were created in conjunction with BAPCPA, although the Judicial Conference had requested 47 permanent positions. Section 1.3 discusses BAPCPA in more detail.

12, Chapter 13, and other. While non-business Chapter 7 cases on average take only 6 minutes of a judge's time, the average Chapter 11 case uses up nearly 8 hours.[16] Following the Judicial Conference, I measure caseload as the weighted number of cases filed per judge in each bankruptcy district. Because the weights are expressed in the number of hours the judge is expected to spend on the case, weighted caseload can be interpreted as the number of hours (per year) the judge would spend administering the particular mix of six bankruptcy case types filed in his bankruptcy district.

**TABLE 1.1**
**BANKRUPTCY CASE WEIGHTS**

| Bankruptcy Type | Expected hours per case |
|---|---|
| Ch. 11 | 7.559 |
| Ch. 12 | 4.04 |
| Business Ch. 7 | 0.397 |
| Ch. 13 | 0.381 |
| Other | 0.194 |
| Non-business Ch. 7 | 0.101 |

On a weighted basis, judges in 1980 had, on average, a total caseload of 503 hours per year. By 2010, that workload had more than doubled to 1,141 hours per year. However, much of that increase came in the first few years of the 1980s, when business bankruptcy filings rose quickly in the aftermath of two closely-spaced economic recessions. Although the number of business bankruptcy filings has fallen since that time, increased numbers of personal bankruptcies have left the overall caseload relatively unchanged. As shown in Figure 1.2, since 1983 total weighted caseload has fluctuated around 1,000 hours per year. In general, total bankruptcy caseload rises during or shortly after economic recessions, and often these increases can be substantial. The average peak-to-trough change in caseload since 1983 is 264 hours, or 25% of the mean caseload per year.

[16] This is an average across all Chapter 11 cases filed in 1989. Since the average size of Chapter 11 firms has increased since this time, it is likely that this underestimates the true total time that Chapter 11 cases consume. Further, it does not account for "mega" Chapter 11 cases such as Lehman Brothers or Enron, whose complexity and public nature costs judges significantly more time.

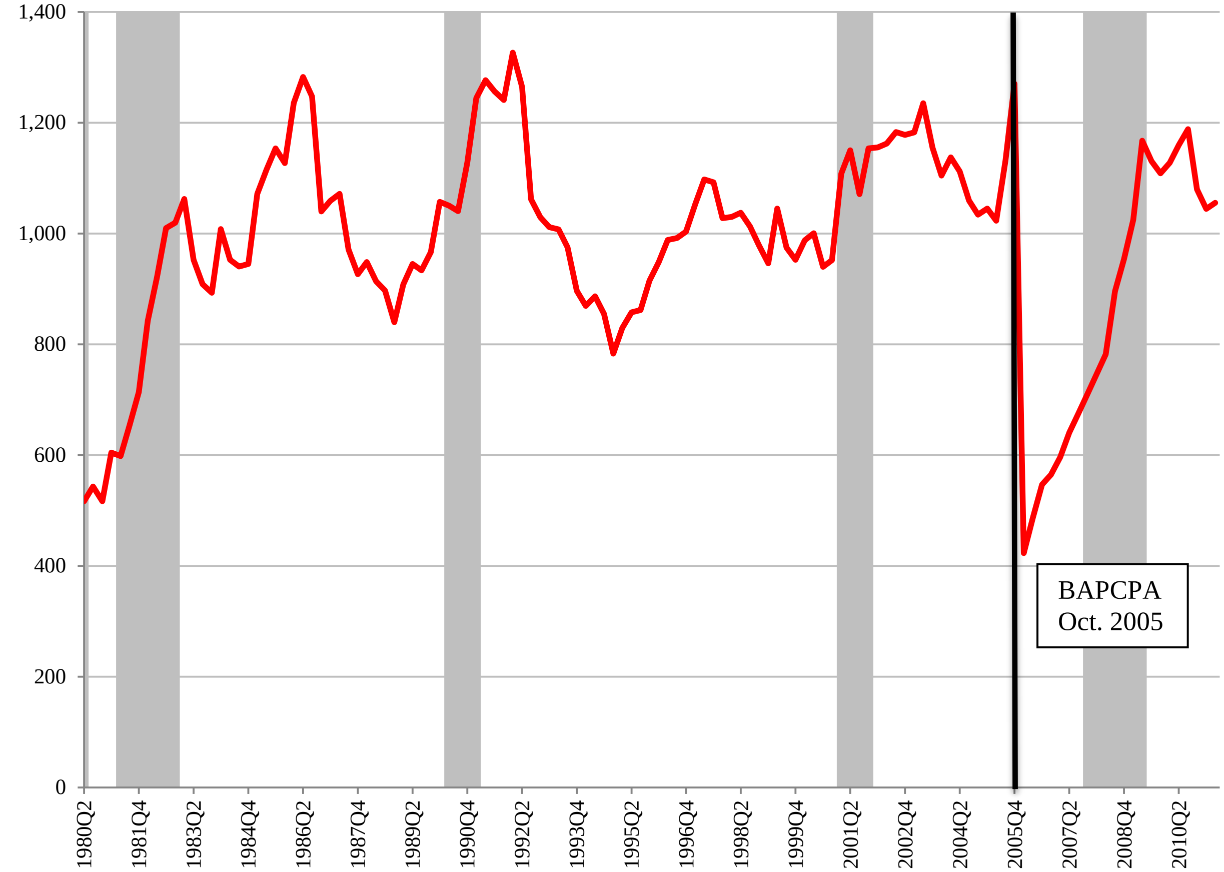



**FIGURE 1.2 - CASELOAD PER JUDGE**

This figure displays the total weighted caseload per judge across the U.S. courts system from 1980Q2 – 2011Q2. The y-axis can be interpreted as the total expected hours a judge will spend on case-work annually. The vertical line identifies the passage of BAPCPA in October 2005, while light-gray shading indicates NBER recessions.

Moreover, there is wide variation in caseload across the 89 bankruptcy districts in the U.S.[17] Taking the average weighted caseload for each district from 1983 – 2011, I find that the standard deviation across districts is 311 hours, or 7.8 40-hour work weeks. At the extremes, the bankruptcy judge in Vermont had an average total workload of 305 hours per year, while the judges of the Western District of Tennessee averaged 1,664 hours per year. More recently, areas that have experienced particularly difficult economic recessions have seen dramatic increases in the caseload required of each judge. For example, since 2009, bankruptcy districts in Nevada (2,161 hours), Middle District of Florida (2,041

[17] There are a total of 94 bankruptcy districts in the U.S. Courts system, but I exclude the Northern Marianas Islands, the Virgin Islands, Guam, and Puerto Rico from my study. In addition, the Western and Eastern Districts of Arkansas share bankruptcy judges, and so I treat them as a single district for this study.

hours), Eastern Michigan (1,865 hours), Northern Mississippi (1,833 hours) and Northern Georgia (1,771 hours) have been particularly stressed.

### 1.3. Identification strategy

Bankruptcy filings typically rise when economic conditions deteriorate, leaving judges with the heaviest workloads during economic recessions. Because of this, a simple comparison of the bankruptcy outcomes of firms that file in busy courts versus those that file in non-busy courts would be confounded by multiple other factors. In particular, during recessions firms have worse outside options for dealing with financial distress. Raising new capital is difficult because credit is tight, asset sales would likely yield lower proceeds due to fire sale pricing, and negotiations with creditors might be more difficult as creditors are potentially facing their own financial issues during recessions. Further, there are potentially selection biases as high-beta firms are more likely to go bankruptcy in recessions. For these reasons, I cannot simply compare firms that file during busy times to those that file when judges have more time available.

In order to identify the causal effect of caseloads on restructuring, I use difference-in-difference specifications that exploit an exogenous shock to caseloads that affected some bankruptcy districts more than others. On April 20, 2005, the Bankruptcy Abuse Prevention and Consumer Protection Act was signed into law by President George W. Bush, although most of the provisions of the Act only applied to bankruptcy cases that were filed on or after October 17 of that same year. BAPCPA was focused mainly on non-business bankruptcies, and, as its name suggests, its primary aim was to prevent abuse of the bankruptcy system by individual filers.

Prior to BAPCPA, individual filers could choose the chapter of bankruptcy under which they filed. BAPCPA instituted a "means test" which forces high-income filers to file for Chapter 13 bankruptcy, where less debt is discharged and future income must be pledged towards paying back creditors, instead of Chapter 7. In addition to the means test, BAPCPA increased the costs of filing for bankruptcy by between 50-70% because of increases in filing fees, lawyer fees, and required debt counseling (United States Government Accountability Office, 2008). Finally, BAPCPA also capped the amount of homestead exemptions at $125,000, which impacted filers in states that traditionally allowed home owners to protect large amounts of home equity.

Because the law was passed in April but not effective until October, there was a window within which individuals could still file under the old law, and this explains the large spike in filings in mid-2005 as individuals rushed to file before the October 17th effective date (Figure 1.1, Panel A). More importantly, though, once the law took effect personal bankruptcy filings dropped to the lowest levels on record, and remained depressed for some time, leaving judges with substantially fewer cases on their dockets that they had to deal with.[18] Bankruptcy judges do not specialize in a particular type of bankruptcy. Because of this, *all* judges were affected by the rush to file and subsequent dearth of consumer bankruptcy filings. In effect, BAPCPA created a natural shock to bankruptcy caseloads faced by courts across the nation.[19]

The drop in personal bankruptcy filings was both large and long-lasting. In 2004-2005, before BAPCPA took effect, the average caseload for bankruptcy judges was 1,059 hours, while in the two years after BAPCPA average caseload was only 566 hours (Table 1.2). In essence, BAPCPA halved the caseloads faced by bankruptcy courts, and filings stayed low well into 2008 (Figure 1.1, Panel A).[20] To put this shock in perspective, the average peak-to-trough change in nationwide caseload prior to BAPCPA was about 265 hours.

Although BAPCPA was focused on personal bankruptcy, it did include three main provisions that affected Chapter 11 restructuring as well. First, the law capped extensions of the exclusivity period – the amount of time that the debtor has the exclusive right to file a plan of reorganization – at 18 months total,

[18] Other research has shown that after BAPCPA individuals found other ways to deal with financial distress besides bankrtupcy, such as defaulting on mortgages (Li, White, & Zhu, 2011; Morgan, Iverson, & Botsch, 2012).

[19] Importantly, bankruptcy law firms typically *do* specialize, and therefore the rush of filings would affect personal bankruptcy law firms but not corporate bankruptcy law firms. Figure A.1 in the appendix lays out how the various parties involved in bankruptcy interact, and shows how the BAPCPA shock feeds through to the judge via household bankruptcy filings only.

[20] When the financial crisis hit in 2008, caseloads began rising quickly, reaching pre-BAPCPA levels in early 2009.

### TABLE 1.2
### CASELOAD SUMMARY STATISTICS

This table reports the distribution of caseload for the eight quarters before and after BAPCPA, as well as the distribution of the non-business share of caseload in 2003 for the 89 bankruptcy districts in my sample. Caseload is measured as the weighted number of filings in each district per quarter per bankruptcy judge, using the weights in Table 1.1. I multiply caseload by four in order to annualize the figures. The weights in Table 1.1 represent the number of hours a judge is expected to spend on a bankruptcy case, and therefore the caseload statistics presented in this table can be interpreted as the total number of hours a judge will spend administering cases per year. *BAPCPA Caselod Drop* is defined as the difference in the average caseload from 2004Q1-2005Q4 and the average caseload from 2006Q1-2007Q4 for each district. In the last two lines of the table, the sample is split into those firms that had below- and above-median share of non-business caseload in 2003, to show that the drop was significantly larger in those districts that had fewer business bankruptcy filings.

| | Obs. | Mean | Std. Dev. | 5th Percentile | Median | 95th Percentile |
|---|---|---|---|---|---|---|
| Non-business Share of Caseload (2003) | 89 | 79.4% | 11.5% | 63.2% | 81.6% | 92.3% |
| Avg. caseload 2004-2005 (pre-BAPCPA) | 89 | 1095.05 | 429.90 | 425.07 | 1107.66 | 1842.90 |
| Avg. caseload 2006-2007 (post-BAPCPA) | 89 | 565.54 | 267.99 | 165.76 | 543.23 | 1063.19 |
| BAPCPA Caseload Drop | 89 | 529.51 | 215.27 | 207.77 | 528.87 | 908.77 |
| Below-median non-business caseload | 45 | 456.54 | 196.30 | 170.56 | 484.20 | 792.15 |
| Above-median non-business caseload | 44 | 604.14 | 210.08 | 321.32 | 566.18 | 1000.40 |

while previously extensions were unlimited. It also limited the window within which the debtor has to decide whether it will assume or reject leases on commercial property. Second, BAPCPA imposed penalties on repeat filers. Firms that re-file for bankruptcy within one year after reorganizing have the automatic stay lifted after 30 days unless the court grants an extension. Third, BAPCPA made "pre-packaged" bankruptcy filings more attractive by allowing the solicitation of votes on the prearranged plan to continue while the firm formally files for bankruptcy.[21]

These alterations to the law did induce a few firms to file for Chapter 11 just before the effective date of October 17th, 2005. In the week before BAPCPA took effect 343 firms filed for Chapter 11, compared with only 45 in the week after. However, it does not appear that BAPCPA altered the Chapter 11 filing rate in an economically significant way (see Figure 1.1, Panel B). By the first quarter of 2006 the number of filings was nearly identical to the number in the third quarter of 2005. Further, this mini "rush to file" is driven completely by the smallest firms that file for Chapter 11. These firms are excluded

[21] See Chapter 2 of Gilson (2010) for a full overview of how BAPCPA affected Chapter 11 bankruptcy.

from my sample (see Section 1.4). In my sample, there is no observable change in the business Chapter 11 bankruptcy filing rate around the passage of BAPCPA.

Because BAPCPA affected some aspects of the Chapter 11 process, and to avoid possible impacts of time effects[22], I do not simply compare cases that were filed before and after the law to test the impact of caseload on bankruptcy outcomes. Instead, I employ a difference-in-differences framework that focuses on bankruptcy districts that were disproportionately affected by the law. Because of BAPCPA's focus on consumer bankruptcies, its passage caused a disproportionately larger drop in caseload in those districts that spend more of their time on non-business bankruptcy filings. I use the share of caseload that stems from non-business filings in 2003 as a measure of how consumer-oriented each court is.[23] A bankruptcy district that spends the majority of its time on personal bankruptcies saw its workload drop by more because of BAPCPA.

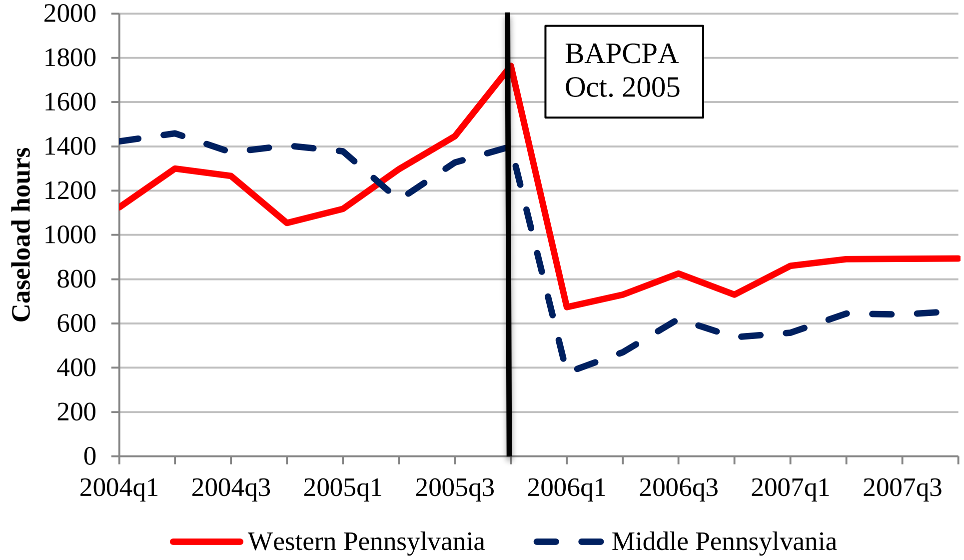
For example, Figure 1.3, Panel A shows the differential impact of BAPCPA in two bordering bankruptcy districts, the Western and Middle Districts of Pennsylvania. Because Western Pennsylvania takes in Pittsburgh, its bankruptcy court is more business-oriented. In 2003, non-business bankruptcies accounted for 67% of total caseload in Western Pennsylvania, while the non-business share of caseload in the Middle District was 83%. Because of this, when BAPCPA passed and the non-business filing rate dropped, caseload dropped by more in the consumer-centric Middle District than in the Western district. Specifically, caseload in the Middle District dropped by about 800 hours after BAPCPA, as compared to a drop of only 485 hours in the Western District.

This pattern holds across for the full sample. Panel B of Figure 1.3 plots the average caseload of consumer-centric bankruptcy districts – defined as those districts that had an above-median non-business share of caseload in 2003 – versus the caseload of the more business-centric courts. Importantly, the two

[22] Baird & Rasmussen (2002) and Bharath, Panchapegesan, & Werner (2010) explore how Chapter 11 is changing over time. My empirical strategy nets out any time effects by comparing firms that filed in the same quarter to each other.

[23] The non-business share of caseload is quite static over time. For example, the cross-sectional correlation between this measure in 1995 and 2003 is 0.76 and significant at the 1% level.

*Panel A: Western and Middle Districts of Pennsylvania*




*Panel B: Average across all business- and consumer-centric districts*

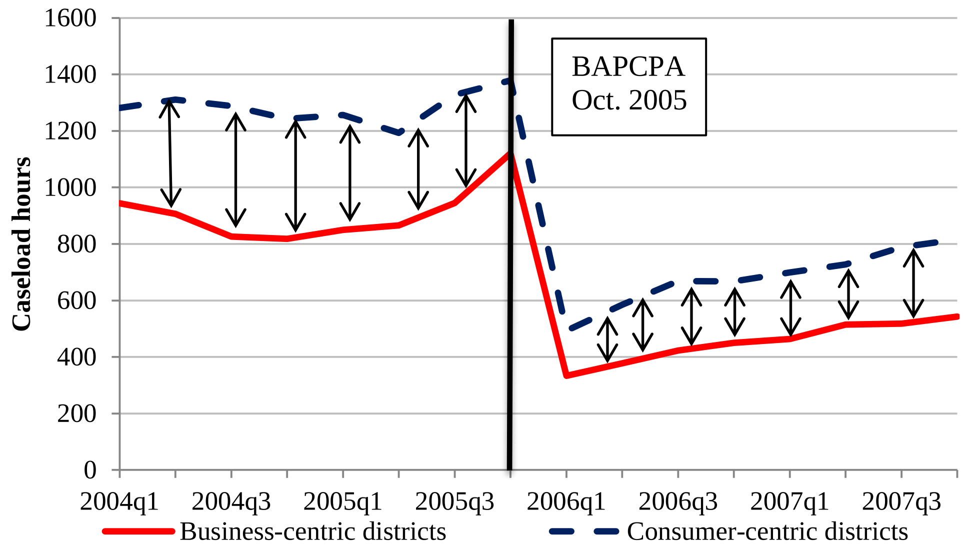



**FIGURE 1.3 - BAPCPA'S EFFECT ON CONSUMER- AND BUSINESS-CENTRIC BANKRUPTCY DISTRICTS**

This figure shows how court caseload evolved in consumer- and business-centric districts from 2004-2007. Panel A uses an example of two neighboring bankruptcy districts: the Western and Middle Districts of Pennsylvania. The Middle District of Pennsylvania spends about 83% of its time on consumer bankruptcy cases, as compared to 67% in the Western District. BAPCPA decreased caseload by substantially more in the consumer-centric Middle District. Panel B shows a similar pattern for all 89 bankruptcy districts. In this chart, districts with an above-median non-business share of caseload are classified as "consumer-centric," while the remaining districts are "business-centric." The average caseload for each group is then plotted in the solid and dotted lines over time. Because BAPCPA disproportionately impacted the consumer-centric groups, the difference between the two lines (indicated by the arrows) shrinks by nearly half after its passage.

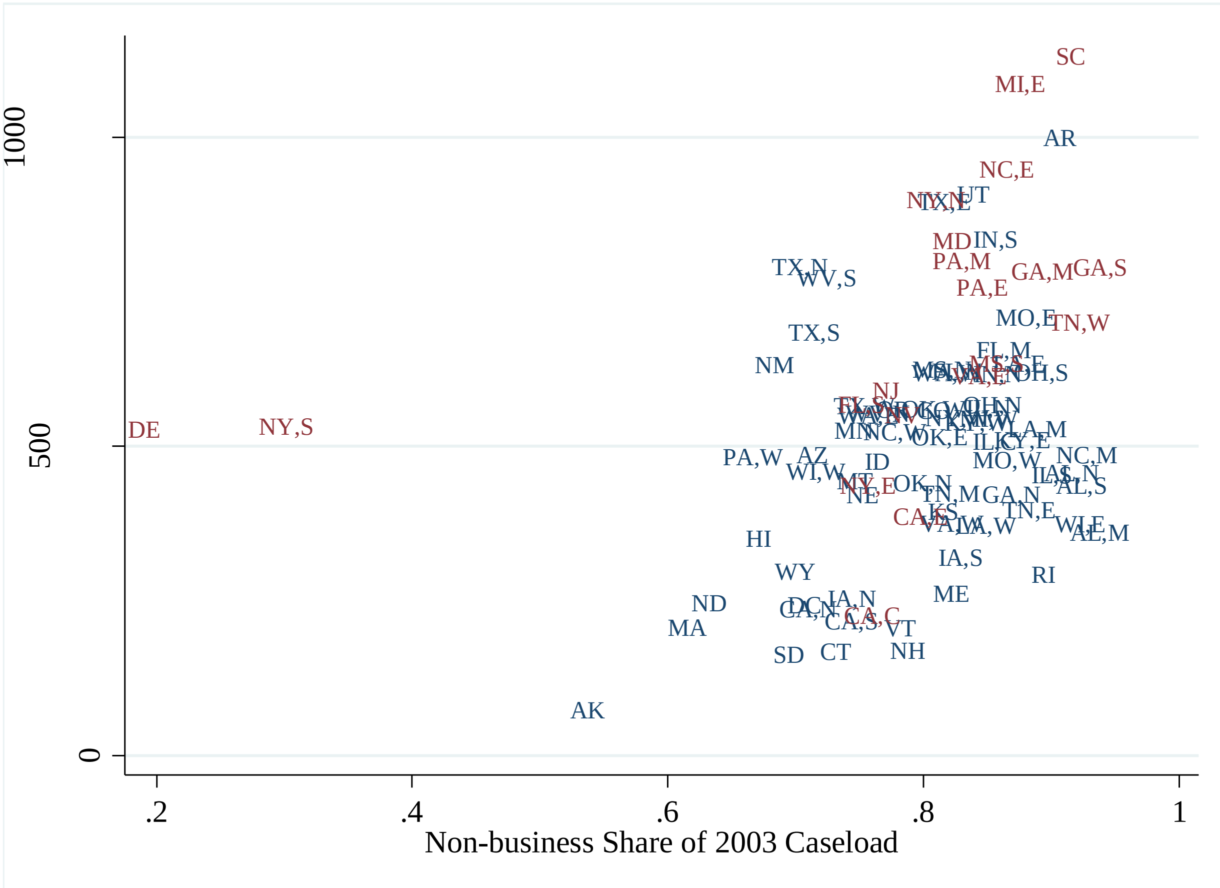



**FIGURE 1.4 - BUSINESS CASELOAD AND THE BAPCPA CASELOAD DROP**

This figure plots the decrease in caseloads due to BAPCPA against the non-business share of caseload in 2003 for each of the 89 bankruptcy districts in my sample. The drop in caseload is calculated as the average caseload in the district during 2004-2005 less the average caseload in 2006-2007. The non-business share of caseload is the share of weighted caseload in 2003 that is due to non-business bankruptcy filings. Districts shown in red also received new judgeships with the passage of BAPCPA, and consequently had larger drops in caseload than would otherwise be expected.

sets have parallel trends before and after BAPCPA, but the consumer-centric courts experienced a larger drop in caseload when BAPCPA took effect. This can be seen even more clearly in Figure 1.4, which shows a scatter plot comparing the drop in caseload from before BAPCPA (2004-2005) to after BAPCPA (2006-2007) against the non-business share of 2003 bankruptcy caseload in each district. The positive relationship between non-business caseload and the impact of BAPCPA is quite robust.[24] This is formally

[24] Delaware and the Southern District of New York show up as clear outliers in Figure 1.4. In Section 1.5.6, I check to make sure that these two districts are not skewing my results.

**TABLE 1.3**
**DECREASE IN CASELOAD DUE TO BAPCPA IN CONSUMER-CENTRIC DISTRICTS**

This table shows that bankruptcy districts that had a higher share of non-business cases in 2003 experienced larger declines in caseload following BAPCPA. In each regression, the dependent variable is the drop in caseload following BAPCPA, defined as the difference in the average caseload from 2004Q1-2005Q4 and the average caseload from 2006Q1-2007Q4 for each bankruptcy district. *Non-Business Caseload (2003)* is the share of weighted caseload in 2003 that was attributable to non-business bankruptcy filings. In the second column, I control for the number of new judgeships that were created by BAPCPA (28 judgeships in 20 districts). In the final column, controls are added for changes in economic conditions and total population from the pre-BAPCPA period (2004-2005) to the post-BAPCPA period (2006-2007). All regressions are estimated by regular OLS, and robust standard errors are reported in parentheses. ***, ** and * indicate statistical significance at 1%, 5%, and 10% level, respectively.

| *Dependent variable:* | *BAPCPA Caseload drop* | | |
|---|---|---|---|
| Non-Business Caseload (2003) | 555.076** | 772.055*** | 714.222*** |
| | (257.969) | (218.711) | (229.337) |
| # of new judges | -- | 108.906** | 146.058*** |
| | | (44.580) | (38.557) |
| Change in unemployment rate | -- | -- | 4.907 |
| | | | (51.278) |
| Change in house price appreciation | -- | -- | -1,037.417*** |
| | | | (252.373) |
| Growth in per capita income | -- | -- | 200.056 |
| | | | (1,000.379) |
| Population growth | -- | -- | 1,043.399 |
| | | | (979.314) |
| Observations | 89 | 89 | 89 |
| R-squared | 0.089 | 0.204 | 0.325 |

tested in a regression setting in Table 1.3. Without accounting for any other variables, a one standard deviation increase in the non-business share of caseload (increase of 11.5 percentage points) results in an additional caseload decrease of 64 hours following BAPCPA, a drop of 12%. This effect persists after controlling for other factors that impacted caseloads. Aside from affecting filing rates for personal bankruptcy, BAPCPA also created 28 new judgeships, which resulted in decreased caseloads per judge in 20 affected districts. Including a control for the number of new judges appointed following BAPCPA strengthens the relationship between non-business caseload share and the decrease in workload. In this specification, a bankruptcy district with a one standard deviation higher share of non-business caseload experienced an additional caseload drop of 90 hours following BAPCPA, or more than 2 full work weeks. Controlling for changes unemployment, house prices, per capita income, and population in each bankruptcy district does not affect the relationship between non-business caseload and the BAPCPA shock. This is important, as it shows that, although caseload is affected by changes in economic conditions (e.g. changes in house prices), the variable that I use to identify the effect of BAPCPA is orthogonal to these factors.

To better visualize which districts were most affected by BAPCPA, Figure 1.5 shows a map that color-codes each bankruptcy district according to the 2003 non-business share of total caseload. Yellow districts are those that are the most consumer-centric and thus saw caseload drop by the most after BAPCPA, while red districts are business-centric and experienced smaller declines in caseload. While it is clear that there is some clustering (e.g. southern states tend to be the most consumer-centric), there is significant variation even across nearby districts, especially in the Northeast and Midwest. In Section 1.5.7, I describe robustness checks that verify that geographic clustering of consumer-centric districts has no effect on my empirical results.

The identification of particular bankruptcy districts that were disproportionately affected by BAPCPA allows me to estimate difference-in-differences regressions of the form:

$$Y_i = \beta(PostBAPCPA_t \times NonBusCaseload_d)_t + \gamma X_i + \tau_d + \mu_t + \varepsilon_i,$$

where $Y_i$ is the outcome of interest for bankruptcy filing *i*, in bankruptcy district *d*, in quarter *t*, and $X_i$is a vector of firm characteristics, $\tau_d$ is a bankruptcy district fixed effect, and $\mu_t$ is a time fixed effect. The coefficient of interest is $\beta$, which captures the impact of filing in the post-BAPCPA period when bankruptcy caseloads were low, in districts which experienced the largest declines in bankruptcy caseload. Because it is more natural to think of an increase in caseload (e.g. when a recession hits) rather than a decrease, in the results presented in Section 1.5 I multiply $PostBAPCPA_t \times NonBusCaseload_d$ by negative one and call this variable "*busy court*". This adjustment does not change the significance or

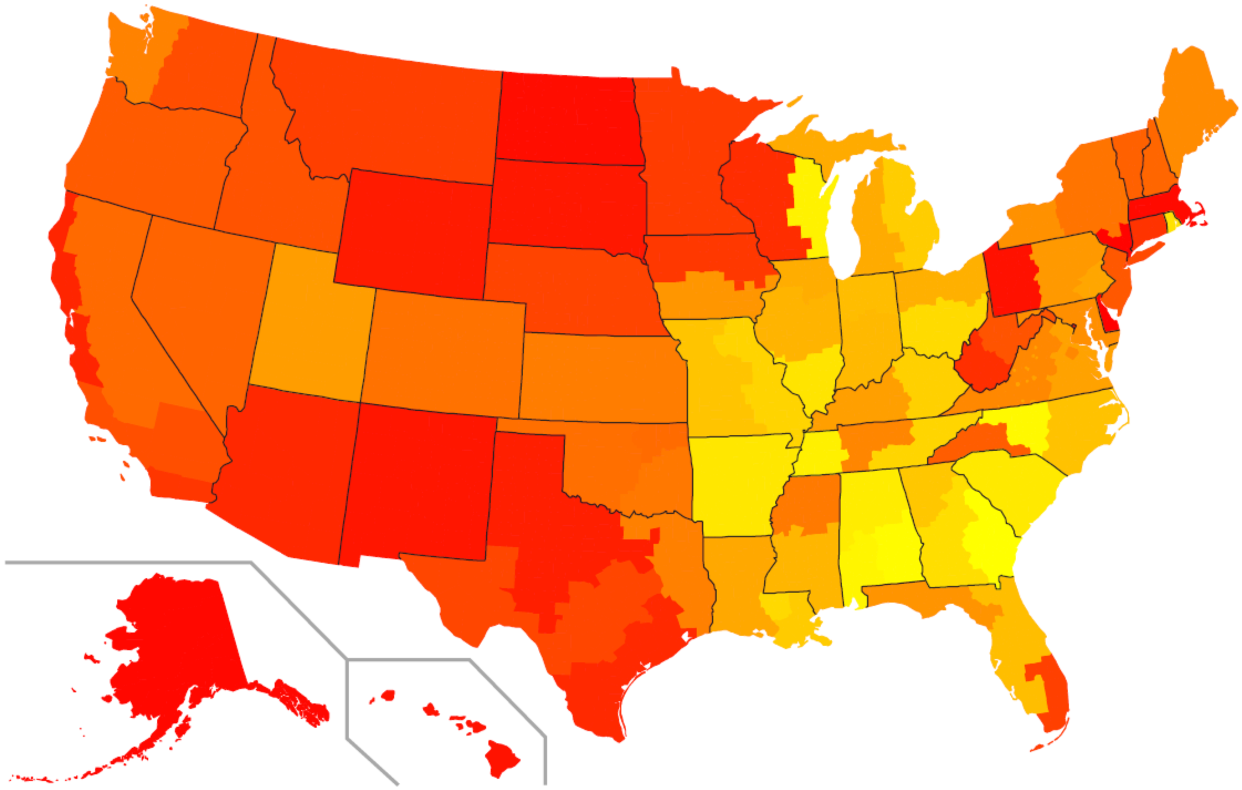


**FIGURE 1.5 - U.S. BANKRUPTCY DISTRICT MAP**
This map displays the 89 bankruptcy districts across the United States. Colors correspond to the share of 2003 caseload that was related to non-business bankruptcy filings. Districts in yellow have the highest non-business share of caseload and hence experienced the largest drop in workload following BAPCPA. Red districts are the most business-centric, while orange districts lie in the middle of the distribution.

magnitude of $\beta$; it is simply easier to interpret in the context of caseload increases due to recessions.[25] I include in my sample firms that filed for Ch. 11 between January 1, 2004 and December 31, 2007, a time period centered on the passage of BAPCPA that ends before main increase in caseload due to the onset of the financial crisis in 2008. Following Bertrand, Duflo, & Mullainathan (2004), in all specifications I cluster standard errors by bankruptcy district in order to account for serial correlation within bankruptcy courts.

[25] Indeed, this is equivalent to estimating the interaction term $PostBAPCPA * BusCaseload$, which identifies business-centric bankruptcy districts instead of consumer-centric districts, since $PostBAPCPA * BusCaseload = PostBAPCPA * (1 - NonBusCaseload) = PostBAPCPA + PostBAPCPA * (-NonBusCaseload) = PostBAPCPA * (-NonBusCaseload) + \mu_t$.

While the above specification captures the overall effect of BAPCPA, one would expect that the impact of a drop in caseload varies depending on the complexity and relative bargaining power of the bankrupt firm. Large firms in particular are more complex (often with hundreds or even thousands of creditors and intricate seniority issues that the judge must deal with) and have a stronger presence in court because they are better-able to hire top-notch lawyers, demand more of their creditors and suppliers, and are also more likely to get press coverage should they go belly up. The smallest firms are much more straight-forward, and in these cases creditors or the trustee may have as much ability to sway the judge as the firm itself. To empirically test whether caseload fluctuations differ by the size of the firm, I add another interaction term to the regression equation:

$$Y_i = \beta_0(PostBAPCPA_t \times NonBusCaseload_d) \\ + \beta_1(PostBAPCPA_t \times NonBusCaseload_d \times \ln(Size_i)) + \gamma X_i + \tau_d + \mu_t + \varepsilon_i,$$

where $Size_i$ is the assets or liabilities of the firm (whichever is largest) at filing. Here, the coefficient $\beta_1$ captures the differential effect that the law had on large firms, while $\beta_0$ captures the estimated impact of BAPCPA on a firm of $Size_i = \$1M$. In order to isolate the true impact of the triple interaction term, in these regressions I include $PostBAPCPA_t \times \ln(Size_i)$ as an additional control in $X_i$. Once again, regression results are reported with the two interaction terms multiplied by -1 in order to put $\beta_0$ and $\beta_1$ in terms of increases in caseload, rather than decreases.

The difference-in-differences estimator shows the causal impact of caseload on bankruptcy outcomes only if the exclusion restriction holds. The confound that one worries about is whether firms that file in consumer-centric bankruptcy districts all changed in a particular way after BAPCPA, and that this change was unrelated to judge caseload. For example, larger firms tend to be located in more urban areas, which also tend to have fewer non-business bankruptcies. If larger firms also became more likely to be reorganized after BAPCPA for reasons unrelated to judge caseload, this would confound the difference-in-difference estimators in the equations above. In Section 1.5.6 I test for these alternate channels by including size-by-time fixed effects and industry-by-time fixed effects. These additional controls allow for there to be varying trends over time for different firm sizes or industries, thus ruling out alternative stories that relate to the composition of firms filing in particular bankruptcy districts. In all cases including these controls do not affect my estimates.

A second possible confound in difference-in-differences estimates is changes in the composition of the sample before and after BAPCPA. If different kinds of firms file for bankruptcy after BAPCPA, then it is possible that my estimated effects are due to changes in the types of bankrupt firms rather than changes in caseload. The fact that the filing rate of Chapter 11 debtors did not change with the passage of BAPCPA suggests that there was a not a significant shift in the propensity of a firm to file for bankruptcy around that time. The composition issue can be further addressed by creating a paired sample that matches firms that filed for bankruptcy before BAPCPA to firms with similar characteristics that filed afterwards. Matching in this way holds the composition of debtors constant before and after BAPCPA. Using the covariates in the vector $X_i$, I create such a matched sample using a propensity score matching model and find that all results continue to hold when the regressions are run on this limited sample.

A final concern relates to forum shopping. Some firms do have discretion in choosing the bankruptcy district where they file, and therefore they could move to a different venue if low or high caseloads in a particular court will adversely affect their outcome. This selection effect could potentially bias my estimates. As described in Section 1.4 below, my sample consists mostly of mid-size firms that do not have a choice in venue. Regardless, I can use the address of the firm to identify debtors that file in non-local bankruptcy districts, and take that as an indicator of firms that picked an alternate venue. I find that 8.7% of the filings in my sample occurred in states other than the home state of the debtor. Omitting these firms from the sample does not alter my results.

### 1.4. Data

I gather information on Chapter 11 bankruptcy filings from LexisNexis Law, which obtains bankruptcy filing data from the U.S. Courts system. I focus on a four-year period surrounding the passage of BAPCPA, from 2004-2007. I end the sample in 2007 to avoid the sharp uptick in caseload that resulted from the financial crisis in 2008 and 2009, and also to have a 3-year period (2008-2010) in which I can examine recidivism into bankruptcy for firms that file near the end of my sample. During this period, LexisNexis has legal information on 14,825 separate business Chapter 11 bankruptcy filings in the 50 states and the District of Columbia. Because LexisNexis' data comes directly from the U.S. Courts, there is essentially 100% coverage of Chapter 11 cases in my data. The benefit of using data from LexisNexis is that it is more easily obtained for the entire, nationwide set of bankruptcies. While several previous bankruptcy studies have used court records to compile data on bankruptcies, due to the difficulty of obtaining this data directly from the U.S. Courts these studies have typically been limited in scope, typically focusing only on a subset of bankruptcy districts or only on public firms, which have more information readily available. To my knowledge, this is the first study to make use of LexisNexis' universal coverage.

The LexisNexis data contains legal information from the U.S. Courts system, including the date the case was filed, the court in which it was filed, the judge assigned to the case, an indicator of whether the filing was voluntary[26] or not, a flag indicating whether the debtor has distributable assets, and status updates on the case. From the status updates, I can determine the outcome of the case: whether it was dismissed from court, converted to Chapter 7, transferred to another court, or reorganized.

I augment this legal information with financial data obtained from Capital IQ and The Deal Pipeline. From these two sources, I obtain the full list of firms that filed for Chapter 11 bankruptcy in their databases, and match them to LexisNexis using bankruptcy case number, filing date, company name, and address. Using this information, I am able to match over 99% of Chapter 11 cases in Capital IQ and The Deal Pipeline during my sample period. From Capital IQ and The Deal Pipeline, I obtain the assets and liabilities reported by the firm at the time of the bankruptcy filing, the industry of the firm, and a flag indicating whether the firm obtained debtor-in-possession (DIP) financing. I also use the text in the description of the bankruptcy to determine whether the firm filed with a pre-arranged or "pre-packaged" bankruptcy plan.

[26] A "voluntary" filing is one in which the debtor filed the petition, while "involuntary" filings are instigated by a creditor or creditors.

Between Capital IQ and The Deal Pipeline, I match a total of 7,223 firms to LexisNexis, which makes up 49% of the 14,825 total bankruptcy filings between 2004 and 2007. To get the final sample, I remove firms which are transferred to other courts or for which there is no exit information in LexisNexis (651 firms). Finally, about half of the filings recorded in Capital IQ or The Deal Pipeline are missing information on industry, assets, or liabilities, reducing my final sample to 3,327 firms, or 22% of all firms that filed for bankruptcy during the sample period.

Because I rely on financial information in Capital IQ and The Deal Pipeline, which do not have information on the smallest firms, the sample used in this study is composed of larger, more complex firms than the overall sample of Chapter 11 filers. For example, 14.1% of the firms in my sample filed jointly with related entities, while only 6.9% of the out-of-sample firms did so. The larger firms in my sample are precisely the cases in which judges are needed to mediate complex negotiations, determine just outcomes, and discern when liquidation is the optimal path for a firm.

Although my sample is limited only to those firms that are in Capital IQ or The Deal Pipeline, it still contains a significant number of smaller firms. Table 1.4 provides summary statistics on the bankrupt firms in my sample. The median firm reports \$2.06 million in assets and \$3.5 million in liabilities at filing, while roughly 10% of my sample has either assets or liabilities of less than \$1 million. On the other extreme the firm at the $90^{th}$ percentile had assets or liabilities of about \$50 million. Sample firms reported being underwater (liabilities > assets) in 61% of the cases at the time of filing, and the median liabilities to assets ratio is 1.31.

Firms may try to under-report the true value of their assets in order to appear more in need of bankruptcy protection than they really are. Because of this, for many debtor firms total liabilities is likely a better measure of the size of the firm than total assets. To overcome this issue, I define a new variable *size*, equal to the maximum of either assets or liabilities at filing, to capture the true scale of the firm. The median firm has a *size* of \$4.4 million, but the distribution contains a few outliers (e.g. Delta Airlines) that skew the average *size* to a much larger \$156.7 million. In all regressions I use the natural log of *size* to

**TABLE 1.4**
**SUMMARY STATISTICS**

This table provides summary statistics of the characteristics of the bankruptcy cases in the sample. Panels A and B pertain to data used on bankruptcy filings. In Panel A, *size* is defined as the maximum of assets or liabilities reported at filing. Panel C provides information on the commercial bank panel data used in Section 1.5.4. All variables in Panel C have been winsorized at the 1st and 99th percentiles.

*Panel A: Continuous variables*

| | Obs. | Mean | Std. Dev. | 5th Percentile | Median | 95th Percentile | Max |
|---|---|---|---|---|---|---|---|
| *Dependent variables:* | | | | | | | |
| Months in Bankruptcy | 3327 | 18.36 | 16.70 | 1.55 | 13.06 | 53.19 | 93.91 |
| Sale Price / Assets | 430 | 0.585 | 2.588 | 0 | 0.226 | 1.127 | 42.00 |
| *Control variables:* | | | | | | | |
| Size at filing | 3327 | $156.65 | $5,303.69 | $0.71 | $4.42 | $112.00 | $301,816 |
| Winsorized size at filing | 3327 | $28.53 | $94.97 | $0.71 | $4.42 | $112.00 | $745 |
| *Other descriptive stats:* | | | | | | | |
| Assets at filing | 3327 | $141.64 | $5,284.58 | $0.05 | $2.06 | $75.00 | $301,816 |
| Liabilities at filing | 3327 | $61.91 | $834.56 | $0.50 | $3.50 | $100.00 | $28,270 |
| Liabilities / Assets | 3291 | 13.61 | 94.86 | 0.33 | 1.31 | 35.00 | 3559 |
| Employees (when available) | 900 | 1,079.82 | 6,656.93 | 8 | 120 | 3,206 | 146,600 |
| # of entities filing jointly | 3327 | 1.677 | 3.952 | 1 | 1 | 4 | 133 |

*Panel B: Binary variables*

| | Obs. | % Obs. |
|---|---|---|
| *Dependent variables:* | | |
| Outcome: | | |
| Reorganized | 3327 | 29.82% |
| Liquidated | 3327 | 36.10% |
| converted to Chapter 7 | 3327 | 28.13% |
| in Chapter 11 | 3327 | 4.36% |
| section 363 sale of all assets | 3327 | 6.85% |
| Dismissed | 3327 | 34.08% |
| Has asset sale | 3327 | 13.01% |
| Re-files for bankruptcy within 3 years | 2089 | 5.18% |
| Reorganized | 953 | 2.52% |
| Dismissed | 1133 | 7.41% |
| Pre-packaged bankruptcy | 3327 | 1.41% |
| Obtained DIP loan | 3327 | 15.87% |
| *Control variables:* | | |
| Liabilities > Assets | 3327 | 61.14% |
| Has related filings | 3327 | 14.10% |
| Distributable assets | 3327 | 92.28% |
| Involuntary filing | 3327 | 1.17% |

**TABLE 1.4** – *continued*

*Panel C: Commercial Banks*

| | Obs. | Mean | Std. Dev. | 5th Percentile | Median | 95th Percentile | Max |
|---|---|---|---|---|---|---|---|
| *Dependent variable:* | | | | | | | |
| Net C&I loan charge-offs (% of total C&I loans) | 29012 | 0.51% | 1.43% | -0.33% | 0.02% | 2.92% | 9.33% |
| *Control variables:* | | | | | | | |
| Annual asset growth | 29012 | 7.67% | 12.00% | -6.32% | 5.42% | 30.12% | 63.27% |
| Net charge-off rate on all other lending | 29012 | 0.16% | 0.34% | -0.43% | 0.06% | 0.70% | 2.44% |

decrease the influence of these outliers, and in Section 1.5.6 I describe robustness checks that verify that these outliers are not driving my results.

Based on the description of the bankruptcy in Capital IQ or The Deal Pipeline, I only find that 47 (1.4%) of the firms in my sample filed pre-packaged plans. When a firm has a pre-packaged plan, the judge has very little to do in the case, and so in most of my empirical results I omit these firms from the sample.[27] Unconditionally, debtors are a bit more likely to be liquidated (36.1%) or dismissed (34.1%) than reorganized (29.8%). Liquidation can come in three different forms, however: conversion to Chapter 7 (28.1%), liquidation directly from Chapter 11 via a "liquidating plan"[28] (4.4%), or the sale of substantially all assets of the firm via a section 363 sale (6.9%). These are not necessarily mutually exclusive; a firm that sells all of its assets in a section 363 sale is often subsequently liquidated via Chapter 7 or a Chapter 11 liquidating plan.

I measure recidivism rates as the propensity to file for either Chapter 7 or Chapter 11 bankruptcy within three years of the original filing date of the bankruptcy. To identify repeat filers, I use information on all business bankruptcy filings (either Chapter 7 or Chapter 11) from LexisNexis from 2004-2010, and

[27] When a debtor files with a pre-packaged plan of reorganization, the judge must still determine that the plan is fair and that it provides higher recovery rates for creditors than if the firm were liquidated under Chapter 7, but this approval is nearly always given. In my sample, all but one of the firms that filed with pre-packaged plans successfully reorganized; the other firm was dismissed from court.

[28] Liquidating plans in Chapter 11 function just like reorganizing plans: they are proposed, voted on, and approved in the same manner. The only difference is that there is no expectation that the debtor will continue operations after exiting.

match the original Chapter 11 filings to future Chapter 7 or 11 filings using tax ids, firm names and aliases, and addresses of the bankrupt firms. Limiting to a 3-year window avoids time effects; firms that file for bankruptcy in 2004 have a much longer time period in which to re-file that those that file in 2007, and will thus naturally have a higher recidivism rate if the whole time period is examined. Also, I do not count firms that re-file within 3 months of their original filing as having re-filed, since these can hardly be considered "separate" bankruptcies; these firms likely exited court due to unusual circumstances (e.g. they were dismissed for failing to file the proper paperwork) and quickly re-filed once the issue was resolved. The 3-month cutoff is somewhat arbitrary; my results are identical if I use a 2-month or 4-month cutoff instead. On average, 2.5% of reorganized firms and 7.4% of dismissed firms re-file for bankruptcy within 3 years of their original filing in my sample.[29]

The sample firms are well-dispersed both geographically and across industries. All 89 bankruptcy districts are represented in the sample, with the median district having 22 bankruptcies and the largest bankruptcy district (Southern District of New York) only composing 6% of the sample. I use reported SIC codes or written industry descriptions from Capital IQ and The Deal Pipeline to classify each firm according to the Fama-French 30 industry classification, and have coverage across all 30 industries.

Both Capital IQ and The Deal Pipeline maintain databases of bankruptcy sales transactions. I use these databases to identify firms which sell assets during the course of bankruptcy, and find that 13% of the firms in my sample have an asset sale recorded. In many cases it is difficult to determine exactly which assets were sold in the auction; the transaction might list a particular piece of property or a division of the company, or it might just list the name of the company. In 53% of the sales (228 cases), however, the phrase "substantially all assets" is used in the description of the asset, signifying that in these cases the entire firm was sold. I mark these firms have having been liquidated completely.

[29] I do not consider firms that are liquidated in my analyses of recidivism, since by and large these firms cease to exist after their original bankruptcy and cannot re-file. Exceptions to this would include firms that are converted to Chapter 7 but later re-instated to Chapter 11 or dismissed from court, or firms which are sold as going concerns to a single buyer and continue to operate as separate entities.

Because recovery rates are not available for private companies, I cannot measure the impact of caseload on creditors directly for each bankruptcy filing. Instead, I turn to regulatory data reported by U.S. commercial banks in the Consolidated Report of Condition and Income (commonly known as the Call Reports). From the end-of-year Call Reports from 2004-2007, I obtain information on the net charge-offs reported by each bank on its commercial and industrial (C&I) lending. Net charge-offs are calculated as the total amount written off during the year less any recoveries received on C&I loans and hence represent the aggregate loss on C&I lending sustained by the bank. For each year, I scale total net charge-offs by the average outstanding amount of C&I loans held by the bank over the course of the year.[30] In addition to this main dependent variable, I also collect information on asset growth and the net charge-off rate on all other lending at the bank. To avoid undue influence of outliers, I winsorize each of these variables at the 1st and 99th percentiles.

The exposure of each bank to the BAPCPA shock depends on its location; banks in consumer-centric districts saw caseloads drop by more after BAPCPA than those located in business-centric districts. Using the FDIC's Summary of Deposits data from 2003, I first determine the share of a bank's deposits that were located in each bankruptcy district in that year. I then calculate the weighted average non-business share of caseload across all bankruptcy districts in which a bank has deposits, using the share of deposits in each district as a weight. This weighted average of non-business caseload then acts as a proxy for the size of the caseload shock experienced by the bank following BAPCPA.[31]

[30] Taking the average across all four quarters helps account for timing issues in the recognition of charge-offs by the bank. Specifically, some of the charge-offs reported at the end of the year will be related to loans that went bad earlier in the year. The appendix gives more information on loan loss accounting, as well as tests using alternative measures of loan losses. Results using alternative measures give similar results.
[31] The appendix contains more detail on LexisNexis' coverage of bankruptcy filings and the variables derived from the data, and the dispersion of cases by industry and bankruptcy district.

## 1.5. The effect of heavy caseload on Chapter 11 restructuring

### *1.5.1. Bankruptcy outcomes: reorganization, liquidation, or dismissal*

In this section, I first focus on estimating the effect that decreased caseloads following BAPCPA had on the outcome for firms in Chapter 11. In general, a firm that files for Chapter 11 bankruptcy can have one of three outcomes:

1. *Reorganization*: a restructuring plan is formed and accepted, previous debtors are paid according to the plan, a new capital structure is put in place, and the debtor emerges from bankruptcy
2. *Liquidation*: the debtor's case is converted to Chapter 7, the debtor is liquidated directly from Chapter 11, or the debtor's assets are sold as part of a Chapter 11 bankruptcy auction
3. *Dismissal*: the case is dismissed and the debtor remains as if no bankruptcy filing had occurred.

Having established in Section 1.3 that bankruptcy districts with fewer business cases were disproportionately affected by BAPCPA, I use the non-business share of caseload as a proxy for the size of the caseload drop and estimate its effect on bankruptcy outcomes using the difference-in-differences methodology outlined in Section 1.3. I exclude from these regressions firms that filed with pre-packaged bankruptcy plans, since the court has little to do in such cases. In these models, I control for:

- The natural log of the *size* of the firm, where *size* is defined as $\max(assets, liabilities)$ at the time of the bankruptcy filing.
- A dummy variable equal to one if liabilities are greater than assets, indicating firms that are more financially distressed. I use a dummy variable rather than the actual liabilities to assets ratio because some firms report very low assets, resulting in extremely high ratios. However, my results are unchanged if I use the liabilities to assets ratio instead of this indicator variable.
- A dummy variable equal to one if the firm had subsidiaries or related entities that filed at the same time.

- A dummy variable equal to one if the firm had non-exempt assets available for distribution to creditors, according to a flag recorded in LexisNexis.
- An indicator of whether the filing was voluntary (filed by the firm) or involuntary (filed by creditors). Only 1.2% of the sample filings were involuntary, but these cases are typically much more likely to be dismissed from court.
- An indicator variable equal to one if the firm obtained DIP financing. Obtaining a DIP loan is important for firms that need cash to continue to operate during bankruptcy proceedings, and is typically associated with a higher likelihood of reorganization (Dahiya, John, Puri, & Ramírez, 2003).
- Fixed effects for 30 Fama-French industries, fixed effects for the quarter in which the firm filed for bankruptcy (there are a total of 16 quarters in my sample period), and fixed effects for the bankruptcy district in which the firm filed (89 districts).

In the results presented in Table 1.5, there are two main coefficients of interest. First, the variable *busy court*, defined as -1 times the interaction of a post-BAPCPA dummy and the non-business share of caseload in the bankruptcy district, captures the effect of filing in districts which experienced the smallest decreases in caseload following BAPCPA. Because my estimates include both industry and quarter fixed effects, the coefficient on *busy court* effectively compares two firms from the same industry that filed for bankruptcy in the same quarter but in districts that had exogenously different caseload due to BAPCPA. The estimates show that Chapter 11 debtors that filed in districts with the heaviest caseloads were significantly more likely to emerge from bankruptcy via reorganization, and instead are less likely to be dismissed from court. As explain in Section 1.2.1 above, dismissal favors creditors by allowing them to seize assets and in most cases is akin to liquidation, especially for small firms. My results show that busy judges are more willing to allow firms to reorganize and emerge from bankruptcy while less-busy judges dismiss more cases from court.

# TABLE 1.5

## THE EFFECT OF CASELOAD ON BANKRUPTCY OUTCOME

This table explores the relation between the change in caseload due to BAPCPA and whether the bankrupt firm was reorganized, liquidated, or dismissed from court. *Busy court* is defined as the interaction of a *post-BAPCPA* dummy, equal to one if the firm filed on or after 17 October 2005, and *-1*non-business caseload*, the share of caseload in 2003 that was derived from non-business filings. *Size* is the maximum of either assets or liabilities reported at the time of filing. The other control variables indicate whether the firm reported liabilities > assets at filing, if the firm had other related entities that filed jointly, if the firm had assets available for distribution to creditors, if the filing was involuntary (filed by a creditor), and if the firm obtained DIP financing. All regressions include 89 district fixed effects, 16 quarter fixed effects, and 30 industry fixed effects. All models are estimated using linear least squares. Standard errors are clustered by bankruptcy district and reported in parenthesis. ***, ** and * indicate statistical significance at 1%, 5%, and 10% level, respectively.

| | | | *Liquidated* | | | | | |
|---|---|---|---|---|---|---|---|---|
| *Dependent Variable:* | *Reorganized* | | *All liquidations* | | *Conversion to Ch. 7* | | *Dismissed* | |
| Busy court | 0.149** | 0.087 | -0.017 | 0.074 | -0.005 | 0.053 | -0.132** | -0.161** |
| | (0.061) | (0.068) | (0.054) | (0.067) | (0.039) | (0.047) | (0.058) | (0.073) |
| Busy court * ln(size) | -- | 0.044** | -- | -0.066*** | -- | -0.039** | -- | 0.022 |
| | | (0.022) | | (0.021) | | (0.016) | | (0.017) |
| Post BAPCPA * ln(size) | -- | 0.013 | -- | -0.029** | -- | -0.003 | -- | 0.016 |
| | | (0.013) | | (0.013) | | (0.010) | | (0.011) |
| Ln(size) | 0.008 | 0.022** | 0.024*** | 0.011 | -0.000 | -0.019** | -0.032*** | -0.033*** |
| | (0.006) | (0.010) | (0.008) | (0.010) | (0.006) | (0.009) | (0.006) | (0.009) |
| Liabilities > assets at filing | -0.015 | -0.015 | 0.070*** | 0.070*** | 0.063*** | 0.063*** | -0.054*** | -0.054*** |
| | (0.019) | (0.019) | (0.019) | (0.019) | (0.017) | (0.016) | (0.020) | (0.020) |
| Group filing | 0.039 | 0.034 | 0.035 | 0.040 | 0.017 | 0.023 | -0.074*** | -0.074*** |
| | (0.029) | (0.029) | (0.025) | (0.025) | (0.027) | (0.027) | (0.027) | (0.027) |
| Distributable assets | 0.218*** | 0.218*** | -0.517*** | -0.518*** | -0.555*** | -0.555*** | 0.300*** | 0.300*** |
| | (0.022) | (0.021) | (0.040) | (0.039) | (0.043) | (0.042) | (0.036) | (0.036) |
| Involuntary | -0.020 | -0.016 | 0.180* | 0.174* | 0.123 | 0.119 | -0.160*** | -0.158*** |
| | (0.095) | (0.095) | (0.091) | (0.091) | (0.095) | (0.096) | (0.058) | (0.058) |
| Got DIP loan | 0.073*** | 0.070** | 0.058** | 0.060** | -0.045* | -0.041* | -0.131*** | -0.131*** |
| | (0.027) | (0.027) | (0.024) | (0.024) | (0.024) | (0.024) | (0.018) | (0.019) |
| Quarter, industry, and district fixed effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 3,280 | 3,280 | 3,280 | 3,280 | 3,280 | 3,280 | 3,280 | 3,280 |
| R-squared | 0.064 | 0.065 | 0.128 | 0.130 | 0.147 | 0.149 | 0.127 | 0.128 |

The second coefficient of interest in Table 1.5 is the impact of the interaction term *busy court*ln(size)*, which tests whether these effects differ by the size of the firm. I find that while all firms are more likely to be reorganized in busy courts, this is particularly true for larger firms. Busy judges will have the hardest time determining the viability of the largest, most complex bankrupt firms, and so it is unsurprising that higher caseloads have the biggest impact on the largest firms. In addition, larger firms are likely better able to lobby a busy judge to allow reorganization: they can better afford high quality lawyers, and the (likely negative) publicity for the judge will be much larger if a large firm is liquidated.[32] The differential impact of caseload on large firms comes through increased liquidations rather than dismissals, which relates to the fact that large firms in general are less likely to be dismissed. While dismissal likely means the death of the firm for small firms, a large firm that is dismissed may be more likely to re-file, file in another district, or find a way to negotiate with its creditors. As can be seen in the coefficients on *ln(Size)* in Table 1.5, large firms are substantially less likely to be dismissed from court, but more likely to be liquidated. When a judge determines that a large firm should not be reorganized, he is likely to choose to liquidate the firm directly. Less-busy judges in particular are more likely to liquidate a firm. All of this effect comes through liquidations via conversion to Chapter 7, rather than liquidating plans in Chapter 11 or 363 sales of all the firm's assets.

There are several ways to quantify the economic magnitude of these estimates. As described in Section 1.3, a one standard deviation increase in the non-business share of caseload (11.5%) is associated with an additional 64.1 hour drop in caseload following BAPCPA.[33] Thus, I estimate that on average, a 64-hour increase in caseload increases the probability of reorganization by $11.5\% * 14.9\% = 1.7\%$, a modest increase from the unconditional mean of 29.8%. However, a 64-hour shock is relatively small compared to many of the caseload changes that occur in bankruptcy courts. The true economic impact of

[32] Judge career concerns have received a fair amount of attention in the academic literature as a possible reason why judges are reluctant to liquidate large firms. Recent examples include LoPucki (2005) and Gennaioli & Rossi (2010).

[33] Because the diff-in-diff regressions do not control for other factors that affect the caseload drop, I use the estimates from the specification which simply regresses business caseload share on the decrease in caseload with no other controls.

changes in caseload can be better understood in the context of typical observed changes in caseload. Nationwide, weighted caseload per judge has on average risen by 305.6 hours in the two years following the mid-point of an economic recession (as defined by the National Bureau of Economic Research), which is 4.77 times larger than the 64.1 hour increase mentioned above. Thus, a rough estimate of the impact of increased filings following economic recessions is that they increase the probability of reorganization by $1.7\% * 4.77 = 8.2\%$, a much more substantial amount.

A caseload shock of 306 hours is on the same order of magnitude of many other standard changes in bankruptcy caseload. Since 1983, the average nationwide peak-to-trough change in caseload has been 264 hours. The standard deviation of nationwide caseload over time (since 1980) is 188 hours. Variation across bankruptcy districts tends to be more substantial. If one ranks the 89 districts by their average caseload since 1980, moving from the district at the 25$^{th}$ percentile (Hawaii) to the 75$^{th}$ percentile (Utah) results in an increased caseload of 457 hours. The standard deviation across all 89 districts is 361 hours. In order to give a sense of the economic magnitude of my estimates, I will continue to use the typical increase in caseload following recessions of 306 hours in the rest of the chapter, following the logic laid out in the paragraph above.[34]

Returning to the impact of caseloads on the outcome of the bankruptcy, I now provide estimates of the size of the impact depending on the size of the firm. The firm at the 10$^{th}$ percentile in my sample has *size* equal to \$1 million, the median firm has *size* of \$4.42 million, and the firm at the 90$^{th}$ percentile has *size* of \$48.9 million. Using this as a guideline, I use firms of *size* \$1 million, \$5 million, and \$50 million to give an idea of how the change in caseloads affects firms of varying sizes. Based on the coefficients in Table 1.5, Table 1.6 shows the estimated impact that a 306-hour increase in bankruptcy caseloads would have on the probability of each bankruptcy outcome:

[34] It is important to note that using a shock of 306 hours makes the assumption that my difference-in-differences estimates are externally valid, i.e. can be applied outside of the difference-in-differences context. One should keep in mind that typical increases in caseload occur when economic conditions deteriorate, when outside factors other than caseload will also affect the outcome variables. The concluding section discusses this further.

**TABLE 1.6**
**IMPACT OF 306-HOUR CASELOAD SHOCK ON BANKRUPTCY OUTCOME**

| | Firm *size* | | |
|---|---|---|---|
| Change in probability of: | $1 million | $5 million | $50 million |
| Reorganization | 4.8 | 8.7*** | 18.2*** |
| Liquidation | 4.1 | -1.8 | -16.0*** |
| Dismissal | -8.9** | -6.9** | -2.2 |

In this and future tables that display the estimated impact of a recessionary rise in caseload, ***, **, and * are used to indicate whether the estimate is statistically different from zero at the 1%, 5%, and 10% level, respectively. These tests are performed using a Wald test of the linear combination $\beta_0 + \beta_1 * \ln(size)$, where $\beta_0$ is the coefficient on *busy court* and $\beta_1$ is the coefficient on *busy court*ln(size)*. Note that it is possible that the effect on large firms is statistically different from the effect on small firms even while neither is statistically different from zero.

1.5.2. *Time in bankruptcy*

Several previous studies have used the time in bankruptcy as an indirect measure of total bankruptcy costs, including Bris et al. (2006), Franks & Torous (1989) and Thorburn (2000). To the extent that increases in caseload force courts to stretch out the proceedings for each bankruptcy case, filings in busier courts could be substantially more costly than those in less-busy courts. Importantly, Bris et al. (2006) find that judges are particularly important determinants of the speed of the bankruptcy case, suggesting that judges have large amounts of leeway in determining the speed at which cases resolve.[35] In Panel A of Table 1.7, I test whether busy bankruptcy courts clog the system and force Chapter 11 debtors to spend a longer amount of time in bankruptcy. For these regressions, I define time in bankruptcy as the number of months between the filing date of the case and the date that a resolution was reached. For reorganizations and dismissals, the resolution date corresponds to the date on which the case was discharged from court. For liquidations, the resolution date is the date on which the case is converted

[35] In one conversation I had with a bankruptcy judge, another judge was singled out as running a "rocket docket" court, in which everything was streamlined in order to minimize the amount of time a case was in court. I indeed find that this is the case in my data: the "rocket docket" judge moved Chapter 11 cases through court almost 5 months faster than his counterparts in the same court.

## TABLE 1.7
## THE EFFECT OF CASELOAD ON TIME IN BANKRUPTCY

This table explores the relation between the change in caseload due to BAPCPA and the duration of the firm's stay in bankruptcy. The dependent variable is the number of months between the bankruptcy filing and the resolution date of the bankruptcy. In Panel A all bankruptcy cases are included, and controls for the outcome of the case. Panel B splits the sample by bankruptcy outcome: reorganized, liquidated, and dismissed. All independent variables are defined as in Table 1.5, with the addition of controls for the outcome of the bankruptcy case in Panel A. For clarity, the key variables that identify the effect of caseload on time in bankruptcy are shaded. All regressions include 89 district fixed effects, 16 quarter fixed effects, and 30 industry fixed effects. All models are estimated using linear least squares. Standard errors are clustered by bankruptcy district and reported in parenthesis. ***, ** and * indicate statistical significance at 1%, 5%, and 10% level, respectively.

*Panel A: All Bankruptcy Cases*

| *Dependent variable:* | *Months in bankruptcy* | |
|---|---|---|
| Busy court | 2.034 | 1.017 |
| | (3.711) | (3.357) |
| Busy court * ln(size) | -- | 0.53 |
| | | (0.737) |
| Post BAPCPA * ln(size) | -- | -1.013** |
| | | (0.393) |
| Ln(size) | 1.644*** | 2.628*** |
| | (0.261) | (0.520) |
| Liabilities > assets at filing | -0.296 | -0.276 |
| | (0.539) | (0.536) |
| Group filing | -0.171 | -0.419 |
| | (0.874) | (0.847) |
| Distributable assets | 4.569*** | 4.619*** |
| | (1.009) | (0.997) |
| Involuntary | 2.016 | 2.045 |
| | (3.919) | (3.982) |
| Got DIP loan | 3.991*** | 3.771*** |
| | (1.000) | (1.007) |
| Liquidated | -9.419*** | -12.989*** |
| | (0.892) | (0.718) |
| Dismissed | -13.036*** | -9.333*** |
| | (0.735) | (0.881) |
| Quarter, industry, and district fixed effects | Yes | Yes |
| Observations | 3,280 | 3,280 |
| R-squared | 0.236 | 0.240 |

**TABLE 1.7** – *continued*

*Panel B: Sample split by bankruptcy outcome*

| *Dependent variable:* | *Months in bankruptcy* | | | | | |
|---|---|---|---|---|---|---|
| Sample: | Reorganized | | Liquidated | | Dismissed | |
| Busy court | 11.069* | 11.915** | -4.189 | -6.743 | -4.951 | -4.928 |
| | (5.892) | (5.052) | (4.332) | (6.586) | (4.107) | (4.410) |
| Busy court * ln(size) | -- | -0.527 | -- | 2.144 | -- | 0.065 |
| | | (2.087) | | (1.507) | | (1.897) |
| Post BAPCPA * ln(size) | -- | -0.019 | -- | -2.332** | -- | 0.195 |
| | | (1.173) | | (0.966) | | (1.786) |
| Ln(size) | 1.482*** | 1.279 | 2.635*** | 5.434*** | 0.832** | 0.715 |
| | (0.551) | (0.787) | (0.426) | (0.702) | (0.357) | (0.846) |
| Liabilities > assets at filing | -0.888 | -0.870 | -1.762* | -1.635* | 1.696** | 1.690** |
| | (1.070) | (1.066) | (0.932) | (0.923) | (0.797) | (0.803) |
| Group filing | -1.464 | -1.395 | -0.559 | -1.307 | 2.116 | 2.120 |
| | (1.606) | (1.579) | (1.352) | (1.330) | (1.719) | (1.717) |
| Distributable assets | -4.592 | -4.612 | 3.451*** | 3.667*** | 5.440*** | 5.449*** |
| | (3.907) | (3.912) | (1.113) | (1.099) | (1.972) | (1.983) |
| Involuntary | 8.790** | 8.732* | 2.351 | 2.036 | -7.294*** | -7.259*** |
| | (4.363) | (4.422) | (5.016) | (5.286) | (2.726) | (2.711) |
| Got DIP loan | -1.504 | -1.462 | 6.365*** | 6.175*** | 8.143*** | 8.162*** |
| | (1.938) | (1.945) | (1.680) | (1.657) | (2.051) | (2.074) |
| Quarter, industry, and district fixed effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 953 | 953 | 1,194 | 1,194 | 1,133 | 1,133 |
| R-squared | 0.131 | 0.131 | 0.222 | 0.247 | 0.101 | 0.101 |

to Chapter 7. Converted cases will remain in court for several months after this date while the trustee oversees the liquidation of the assets, but at this point the judge has little left to do on the case, as the decision to liquidate has already been made.

I find that there is no average effect of caseload on time in bankruptcy. This is remarkable, as it suggests that judges who are exogenously busier than others spend less time per case (or longer hours in court each day), rather than extending the total amount of time a firm is in court. But, while I find no overall effect of caseload on time in bankruptcy, this isn't necessarily true for all firms.

In Panel B of Table 1.7 I report regressions that repeat the time in bankruptcy regression for the subsets of firms that were reorganized, liquidated, or dismissed. I find that firms that reorganize in busy courts tend to have longer stays in bankruptcy, while firms that are liquidated or dismissed spend slightly less time in bankruptcy. This suggests that busy judges optimize their time by taking longer with reorganizations and making up for this with quicker liquidations or dismissals. These effects are attenuated slightly for larger firms.

In terms of economic magnitude, the 306-hour average rise in caseload following a recession would be expected to have the following impact on bankrupt firms:

**TABLE 1.8**
**IMPACT OF 306-HOUR CASELOAD SHOCK ON TIME IN BANKRUPTCY**

| Increase in # of months in bankruptcy | Firm *size* | | |
|---|---|---|---|
| | \$1 million | \$5 million | \$50 million |
| All cases | 0.56 | 1.03 | 2.17 |
| Reorganizations | 6.56** | 6.09* | 4.96 |
| Liquidations | -3.71 | -1.81 | 2.80 |
| Dismissals | -2.71 | -2.66 | -2.52 |

Given that the median reorganization in my sample takes 23.1 months, the above table estimates a 26% increase in reorganization times with a 306-hour increase in caseload. For reference, the median liquidation lasts just 10.6 months and the median dismissal is in court for 7.9 months. Taken together, these results suggest that, although busy judges allow firms to reorganize more often, these reorganizations typically take significantly longer and are thus more costly overall.

1.5.3.*Recidivism*

Ideally, an efficient bankruptcy court would separate those firms that are economically viable from those that are not in the least possible time, and then ensure that the firms that leave court have a good chance of not falling back into bankruptcy. I have already shown that firms that eventually reorganize in busy courts take longer to exit, suggesting that efficiency is reduced at least for these firms. In this section I look more closely at the post-bankruptcy performance of firms that pass through busy bankruptcy courts.

## TABLE 1.9
## THE EFFECT OF CASELOAD ON RECIDIVISM

This table explores the relation between the change in caseload due to BAPCPA and the likelihood a firm re-files for bankruptcy. The dependent variable is equal to one if the firm filed for either Chapter 11 or Chapter 7 bankruptcy within three years of its original bankruptcy filing, but more than 3 months after that date. All independent variables are defined as in Table 1.5, with the addition of a dummy variable equal to one if the firm's original filing was dismissed from court. For clarity, the key variables that identify the impact of caseload are shaded. All regressions include 89 district fixed effects, 16 quarter fixed effects, and 30 industry fixed effects. All models are estimated using linear least squares. Standard errors are clustered by bankruptcy district and reported in parenthesis. ***, ** and * indicate statistical significance at 1%, 5%, and 10% level, respectively.

| *Dependent Variable:* | *Re-filed for bankruptcy within 3 years* | | | |
|---|---|---|---|---|
| Sample: | Reorganized | | Dismissed | |
| Busy court | 0.000 | 0.021 | 0.368*** | 0.413*** |
| | (0.027) | (0.035) | (0.131) | (0.130) |
| Busy court * ln(size) | -- | -0.011 | -- | -0.073** |
| | | (0.018) | | (0.036) |
| Post BAPCPA * ln(size) | -- | 0.007 | -- | -0.074** |
| | | (0.008) | | (0.036) |
| Ln(size) | 0.003 | -0.006 | 0.002 | 0.016 |
| | (0.006) | (0.006) | (0.005) | (0.013) |
| Liabilities > assets at filing | 0.006 | 0.007 | -0.029** | -0.027** |
| | (0.009) | (0.010) | (0.013) | (0.012) |
| Group filing | 0.006 | 0.008 | -0.037 | -0.037 |
| | (0.015) | (0.015) | (0.025) | (0.026) |
| Distributable assets | 0.023 | 0.022 | -0.045 | -0.047 |
| | (0.015) | (0.015) | (0.066) | (0.067) |
| Involuntary | -0.045** | -0.047** | -0.074** | -0.080** |
| | (0.019) | (0.019) | (0.036) | (0.037) |
| Got DIP loan | 0.023 | 0.026 | 0.033 | 0.032 |
| | (0.020) | (0.021) | (0.049) | (0.048) |
| Quarter, industry, and district fixed effects | Yes | Yes | Yes | Yes |
| Observations | 953 | 953 | 1,133 | 1,133 |
| R-squared | 0.043 | 0.048 | 0.069 | 0.073 |

I test whether the drop in caseload following BAPCPA affected the probability that a firm re-files for bankruptcy (either Chapter 11 or Chapter 7) within 3 years of (but more than 3 months after) its original filing date.[36] In this analysis I only consider firms that are either reorganized or dismissed from court, as liquidated firms cease to exist and therefore cannot re-file for bankruptcy. Results are presented in Table 1.9. I find that busier courts see significantly higher recidivism. However, this effect is concentrated among firms that are dismissed from court, while debtors that are reorganized in busy courts do not appear to have higher recidivism rates. In addition, the effects appear to be the strongest for smaller firms. An increase in bankruptcy caseloads of 306 hours would have the following impact on the recidivism rates for firms of various sizes:

**TABLE 1.10**
**IMPACT OF 306-HOUR CASELOAD SHOCK ON RECIDIVISM**

| Increase in probability of re-filing withing 3 years | Firm *size* | | |
|---|---|---|---|
| | $1 million | $5 million | $50 million |
| All cases | 7.76*** | 5.81** | 1.07 |
| Reorganizations | 1.16 | 0.18 | -2.19 |
| Dismissals | 22.74*** | 16.27** | 0.55 |

These estimated impacts are quite large; the unconditional probability of a dismissed firm re-filing for bankruptcy within 3 years is only 7.4%, suggesting that the 306-hour shock to caseload more than doubles the recidivism rate for the median firm.

The fact that firms that reorganize in busy courts are no more likely to re-file for bankruptcy is somewhat surprising given the results in Section 1.5.1, which show that busy judges tend to allow more reorganizations and fewer dismissals. If more marginal firms are being reorganized, one might expect that more of them would re-encounter financial distress and end up in bankruptcy once again. One possibility is that the 3-year horizon is too short to find an effect for reorganized firms, which likely take longer to re-enter financial distress than dismissed firms. In particular, results in Section 1.5.2 show that firms that reorganize in busy courts take longer to exit their initial bankruptcy, leaving a shorter window

[36] As mentioned previously, I do not count a firm as having re-filed if it files again within three months of its original filing date, as such filings are likely due to cases in which the firm was dismissed on a technicality and then subsequently re-filed once the problem was rectified.

before the end of the 3-year horizon within which the re-filing might take place.[37] It is also possible that a high percentage of reorganized firms continue to experience financial distress outside of court, even if they do not file for bankruptcy again, as documented in previous research (Chang & Schoar, 2007; Gilson, 1997; Hotchkiss, 1995; Morrison, 2005). On the other hand, it is possible that the quality of restructurings in busy courts is equally as high as that of less busy courts, albeit at elevated costs due to longer stays in bankruptcy. Regardless, within a 3-year window, it does not appear that the exogenous shock to caseload resulted in higher recidivism for firms that reorganize in busier courts.

Meanwhile, dismissed firms re-file at significantly higher rates. There are at least three reasons why this could be the case. First, if busy judges tend to be more pro-debtor, as argued previously, then a firm which gets dismissed from court might be more willing to try re-filing in the busy court in hopes of getting a more favorable outcome the second time in court. Second, busy judges may be unwilling or unable to spend the time necessary to find proper cause for dismissal, thereby making it easier for debtors to appeal the decision or fix the issue that led to the initial dismissal and re-file for bankruptcy protection shortly thereafter. Third, it is possible that a higher portion of the firms that busy judges dismiss from court are viable entities in need of Chapter 11 protection in order to restructure.

Two further tests can shed some light on the mechanism that drives higher recidivism in busy courts. First, defining recidivism to only include re-filings that occur more than 12 months (but still less than 3 years) after the initial filing does not alter the economic magnitude or statistical significance of the results. Thus, the high recidivism rate among firms dismissed from busy courts is not due to quick re-filings that occur less than a year after the initial filing, which casts doubt on the idea that the recidivism effect is driven by firms dismissed by busy judges only because of technicalities or firms that quickly re-file in busy courts in hopes of getting a more lenient judge the second time through. Second, the recidivism effect is driven completely by re-filings for Chapter 11 (so-called "Chapter 22" bankruptcies, which account for a little more than half of the re-filings in my sample), rather than firms who file for

[37] I cannot test longer horizons, as my data end in December 2010.

Chapter 7 in their second filing. This shows that the effect is not being driven by unviable firms that choose to liquidate in court after being initially dismissed from busy courts.[38] Rather, elevated recidivism in busy courts comes from dismissed firms that survive for at least a few months and then attempt to restructure in Chapter 11 once again.

Regardless of whether high recidivism among dismissed firms in busy courts reflects debtors seeking to take advantage of pro-debtor courts or firms which were initially dismissed that could truly benefit from bankruptcy protection, increased recidivism likely drives up both direct and indirect costs of financial distress for these firms, since it drags out the legal process as well as the period of financial distress. Because the value of equity in these firms is at or near zero, the bulk of these costs will be borne by the original creditors of the firm.

*1.5.4. Bank charge-offs*

If busy courts impose higher costs on restructuring firms, these costs will be largely passed on to creditors, since these firms have little or no equity. I use net charge-offs on commercial and industrial (C&I) loans reported by commercial banks as a measure of the total default costs borne by banks. Banks are the main creditors for many small and mid-sized businesses (Petersen & Rajan, 1994), and since the majority of C&I loans are unsecured one would expect losses to be concentrated in this lending.[39]

As described in Section IV, I use a bank's exposure to bankruptcy districts with lower non-business caseload as a proxy for banks that experienced exogenously busier bankruptcy courts post-BAPCPA. Essentially, banks whose branches are located in more consumer-centric bankruptcy districts are likely to lend to businesses that are also located in those districts, and thus these banks would have seen caseloads drop by the largest amount after BAPCPA. In Table 1.11, I report panel regressions that contain annual data for 7,741 commercial banks from 2004-2007. In these regressions, the dependent

[38] For brevity, the results from these two tests are unreported, but are available from the author by request.

[39] According to the Survey of Terms of Business Lending, produced by the Federal Reserve Board of Governors, about 60% of C&I lending is unsecured. Commercial Real Estate (CRE) loans, the other major category of business lending, are typically secured and thus more insulated from default costs. Consistent with this, in unreported regressions, I find that increases in caseload are not significantly related to charge-offs on CRE loans.

## TABLE 1.11
## THE EFFECT OF CASELOAD ON C&I LOAN CHARGE-OFFS

This table shows how changes in caseload affected the performance of commercial and industrial (C&I) loans held by commercial banks. These panel regressions use regulatory data reported by commercial banks at year-end from 2004-2007. The dependent variable is defined as the total charge-offs on C&I loans reported by the bank during the calendar year less any recoveries received on C&I loans, as a percentage of the average total outstanding balance of C&I loans held by the bank over the year. *Busy court* is defined as the interaction of a *post-BAPCPA* dummy, equal to one for all 2006 and 2007 observations, and *-1*non-business caseload*. Because some banks have branches in multiple bankruptcy districts, *non-business caseload* in this table is defined as the weighted average non-business share of court caseload across all districts in which the bank had deposits in 2003. The share of deposits held in each bankruptcy district serves as the weight in this average. *Asset growth* is defined as the log difference in assets from the previous year. *Net charge-off rate on all other loans* is defined similarly to the dependent variable. In the second and third columns controls are added for local economic conditions. All regressions include fixed effects for the 7,741 banks included in the sample as well as year fixed effects. All models are estimated by OLS. Standard errors are clustered by bank to account for serial correlation across years, and are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

| *Dependent Variable:* | *Net charge-offs on C&I loans (% of total C&I loans)* | | |
|---|---|---|---|
| Busy court | 0.375** | 0.437** | 1.151 |
| | (0.188) | (0.194) | (0.729) |
| Busy court * ln(assets) | -- | -- | -0.127 |
| | | | (0.120) |
| Post BAPCPA * ln(assets) | -- | -- | -0.095 |
| | | | (0.095) |
| Asset growth | -0.395*** | -0.382*** | -0.379*** |
| | (0.096) | (0.097) | (0.097) |
| Net charge-off rate on all other loans | 0.673*** | 0.664*** | 0.663*** |
| | (0.067) | (0.068) | (0.068) |
| Ln(per captia income) | -- | -0.822 | -0.848 |
| | | (0.549) | (0.552) |
| Ln(population) | -- | -2.336*** | -2.387*** |
| | | (0.756) | (0.757) |
| Unemployment rate | -- | 0.067** | 0.067** |
| | | (0.030) | (0.030) |
| House price appreciation | -- | -0.194 | -0.186 |
| | | (0.226) | (0.228) |
| Fixed effects: | | | |
| Bank | Yes | Yes | Yes |
| Year | Yes | Yes | Yes |
| Observations | 29,012 | 29,012 | 29,012 |
| R-squared | 0.022 | 0.023 | 0.023 |

variable is total net charge-offs on C&I loans reported by the bank in a particular year, scaled by the average total outstanding C&I lending reported across the four quarterly reports during the year. I use the average of C&I lending over the year to give a better measure of the total amount of C&I lending typically done by the bank, and to help account for the fact that credit losses can be reported with a lag. However, my results are unchanged if I scale by C&I lending reported at the end of the year, or averages over longer periods of time.[40] In all specifications I include both bank and year fixed effects, and cluster the standard errors by bank in order to account for serial correlation within each bank. I also control for the asset growth at each bank and the net charge off rate on all other loans. These variables control for the overall growth of the bank and its overall loan performance during the year. I winsorize all bank-level variables at the 1st and 99th percentiles to prevent undue influence from outliers.

Consistent with the idea that busy bankruptcy courts impose higher restructuring costs, I find that banks that were located in exogenously busier bankruptcy courts saw higher business loan charge-offs relative to banks in less-busy courts. This effect is unchanged if I add controls for the general economic conditions where each bank was located, showing that this effect is orthogonal to any effects of the general economy on loan defaults.[41] Although estimated imprecisely, the results also suggest that charge-offs increase in particular for smaller banks when caseload rises.[42] This result parallels the finding that busy courts tend to be pro-debtor in particular for larger firms. In this case, the negative effects of caseload appear to be borne mostly by smaller banks, which may lack the resources needed to serve on creditor's committees or lobby the court in their favor. In terms of economic magnitude, a 306-hour

[40] Scaling charge-offs by total C&I lending makes this measure an estimate of the probability of default multiplied by the loss given default on C&I loans, i.e. total expected losses. Because busy bankruptcy courts likely affect just the loss given default (not the probability of default), ideally I would use credit losses scaled by the total amount of defaulted loans as the dependent variable in these regressions. However, getting a clean measure of loss given default is not possible from the Call Reports. The appendix gives more detail on this issue, and shows that two alternative proxies for loss given default produce nearly identical results.

[41] These economic indicators are all first calculated for each bankruptcy district using county-level data weighted by the population of each county. Then for each bank, I take the weighted average across all bankruptcy districts in which the bank had deposits, using the amount of deposits in each district as the weight.

[42] This result is not statistically significant. Using two alternative measures of loan charge-offs, in the appendix I do find significant differences between large and small banks.

increase in caseload is estimated to increase net C&I loan charge offs by an average of 24 basis points, which is a 47% increase from the mean of 51 basis points, or 0.17 standard deviations.

### 1.5.5. *Bankruptcy Sales and DIP Financing*

Asset sales are an important feature of the bankruptcy process. Through Section 363 of the Bankruptcy Code, the debtor firm is able to sell some or all of its assets to a third party without the need of creating a plan of reorganization and going through the voting process, although these sales must still be approved by the court. In general, the judge must verify that there is a "good business reason" for the sale (Wolf, Charles & Lees, 2010).

One of the main benefits of 363 sales is that they bring cash to the firm much more quickly than a traditional reorganization plan. Because of this, 363 sales occur more often under emergency circumstances when firms need cash quickly and cannot bring in outside capital through DIP lending.[43] Thus, when the bankruptcy process is expected to be drawn out, such as when bankruptcy caseloads are high, more asset sales should be expected. Further, busy judges are also more likely to approve asset sales, since they typically speed up the bankruptcy process by removing the need for complex debtor-creditor negotiations and detailed reorganization plans.

Table 1.12, which returns to the bankruptcy filings data, shows that this is the case. After BAPCPA, the courts that experienced the largest drop in caseload also had the largest decrease in the share of cases that had 363 sales. My estimates suggest that the rise in caseload after a recession would increase asset sales by 4.7 percentage points, a 36% increase over the unconditional mean of 13%. The impact does not vary much depending on the size of the firm, although it appears to be greatest for small firms (though the difference between large and small firms is statistically insignificant). This makes sense, since small firms have a harder time accessing outside capital and therefore would more likely have to resort to asset sales in cases when the bankruptcy filing drags on for a long period of time.

[43] Lehman Brothers, Chrysler and General Motors are good examples of this motive. In each case the judge approved a quick asset sale because the firms' value as a going concern was diminishing like a "melting ice cube," and they had little access to outside funding at the time.

## Table 1.12
### The effect of caseload on asset sales and DIP lending

This table explores the relation between the change in caseload due to BAPCPA and the need to raise capital during bankruptcy. In the first two columns, the dependent variable is equal to one if the firm sold any assets in bankruptcy. In the middle two columns the dependent variable is the sale price scaled by the assets of the firm, for this firms that had at least one asset sale. In the final two columns the dependent variable is equal to one if the firm obtained debtor-in-possession financing. All control variables are defined as in Table 1.5, with the addition of a control for whether the asset sale was for substantially all of the assets of the firm. For clarity, the key variables that identify the impact of caseload are shaded. All regressions include 89 district fixed effects, 16 quarter fixed effects, and 30 industry fixed effects. All models are estimated using linear least squares. Standard errors are clustered by bankruptcy district and reported in parenthesis. ***, ** and * indicate statistical significance at 1%, 5%, and 10% level, respectively.

| *Dependent Variable:* | *Has asset sale* | | *Sale price / assets* | | *Obtained DIP Loan* | |
|---|---|---|---|---|---|---|
| Busy court | 0.086** | 0.105** | -0.191 | -3.098 | 0.110 | 0.110 |
| | (0.038) | (0.043) | (0.660) | (2.474) | (0.067) | (0.075) |
| Busy court * ln(size) | -- | -0.012 | -- | 1.105 | -- | -0.002 |
| | | (0.017) | | (0.796) | | (0.016) |
| Post BAPCPA * ln(size) | -- | 0.004 | -- | 0.029 | -- | -0.027* |
| | | (0.009) | | (0.202) | | (0.014) |
| Ln(size) | 0.053*** | 0.044*** | -0.525** | -0.189* | 0.090*** | 0.108*** |
| | (0.005) | (0.008) | (0.254) | (0.096) | (0.005) | (0.007) |
| Liabilities > assets at filing | -0.007 | -0.007 | -0.727* | -0.753* | 0.021* | 0.022* |
| | (0.012) | (0.012) | (0.434) | (0.431) | (0.012) | (0.012) |
| Group filing | 0.080*** | 0.083*** | 0.272 | 0.216 | 0.105*** | 0.101*** |
| | (0.020) | (0.021) | (0.236) | (0.219) | (0.019) | (0.019) |
| Distributable assets | 0.031*** | 0.031*** | -0.122 | -0.301 | 0.016 | 0.016 |
| | (0.011) | (0.011) | (0.354) | (0.390) | (0.014) | (0.014) |
| Involuntary | 0.086 | 0.085 | 0.084 | 0.242 | -0.006 | -0.005 |
| | (0.068) | (0.068) | (0.292) | (0.278) | (0.090) | (0.089) |
| Got DIP loan | 0.259*** | 0.260*** | 0.463 | 0.584 | -- | -- |
| | (0.028) | (0.027) | (0.455) | (0.497) | | |
| Substantially all assets sold | -- | -- | 0.426 | 0.503* | -- | -- |
| | | | (0.281) | (0.299) | | |
| Prepackaged bankruptcy | -- | -- | -- | -- | 0.162** | 0.160** |
| | | | | | (0.069) | (0.068) |
| Quarter, industry, and district fixed effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 3,280 | 3,280 | 422 | 422 | 3,327 | 3,327 |
| R-squared | 0.258 | 0.259 | 0.193 | 0.229 | 0.262 | 0.265 |

Firms that are forced to sell assets should also be expected to have to sell at lower prices (Shleifer & Vishny, 1992, 2011). While data from Capital IQ and The Deal Pipeline does contain prices on the bankruptcy transactions, it is difficult to measure whether these prices are discounted from full value because I cannot observe exactly which assets are sold. As a proxy, I scale the selling price by the total assets of the firm, and test whether 363 sales that take place in busy courts have lower price-to-asset ratios than those that are in less-busy courts. This is a very rough proxy, as it is driven not only by "fire sale" prices but also by the amount of assets the firm is selling. For example, a firm that is selling substantially all of its assets will have a higher price-to-asset ratio than a firm that is selling only a small piece of the business, regardless of whether either firm is selling at discounted prices. I control for this to the extent possible by including a dummy variable indicating whether the transaction noted that the firm is selling substantially all assets.[44] In Table 1.12 I test whether the sale price-to-asset ratio is affected by bankruptcy caseload for the 422 sales in my sample. I fail to find a strong relationship between sale prices and court caseload, likely due to a lack of statistical power and imprecise measurement. However, the estimates are in the anticipated direction: small firms, which sell more often when courts are busy, also sell at lower prices when courts are busy. Large firms appear to be able to either find buyers willing to pay higher prices, or can find enough cash to wait through longer bankruptcy periods without selling assets.

Selling assets raises is one way that cash-strapped debtors can raise capital. An alternative method of gaining cash is through the issuance of a DIP loan, which can provide the working capital necessary to maintain operations through a potentially longer bankruptcy stay. The final two columns of Table 1.12 test whether firms in busy bankruptcy courts are more likely to obtain DIP financing. While the coefficient is in the anticipated direction (debtors in busy courts are more likely to get a DIP loan), the estimated effect is not quite statistically significant (p-value=0.103).

[44] If I restrict the regression to the subsample of sales in which substantially all assets are sold I find similar coefficient estimates.

While the statistical precision of these estimates is not overwhelmingly strong, all of the estimates in Table 1.12 point in the direction that increases in caseload force bankrupt firms to obtain excess cash, either through asset sales or debtor-in-possession financing. A summary of the impact of a 306-hour increase in bankruptcy caseloads on the propensity to sell assets, on the sale price / asset ratio and on the propensity of obtain DIP financing is as follows:

**TABLE 1.13**
**IMPACT OF 306-HOUR CASELOAD SHOCK ON ASSET SALES AND DIP FINANCING**

| | Firm *size* | | |
|---|---|---|---|
| | $1 million | $5 million | $50 million |
| Increase in probability of having asset sale | 5.78** | 4.72** | 2.13 |
| Change in price / asset ratio | -1.71 | -0.73 | 1.65 |
| Increase in probability of DIP financing | 6.06 | 5.88 | 5.45 |

It is important to keep in mind that my sample period is 2004-2007, a time when it was relatively easy to obtain credit and when merger & acquisition activity was quite robust. Using BAPCPA for identification is nice because it allows me to focus directly on an exogenous shock to judge time constraints. However, typically courts become crowded during economic recessions, when credit is tight and M&A activity is depressed. In my sample, I find that firms are able to compensate for longer bankruptcy stays by selling assets or obtaining DIP financing, but in recessionary periods they may not be able to find a willing buyer for their assets or a DIP lender. If this is the case, then the impact of heavy caseloads in recessions is likely larger than I have estimated. Rather than obtaining DIP financing, firms could well be forced to sell assets in 363 sales (as Chrysler and General Motors did in 2009) or simply liquidate completely. Further, asset sales in recessions are also sub-optimal due to deeply discounted "fire sale" prices and a lack of buyers who can best use the assets (Shleifer & Vishny, 1992). In this way, difficult credit and M&A environments during recessions likely exacerbate the costs of busy bankruptcy courts.

### 1.5.6. *Robustness*

As Table 1.4 shows, there are a few very large firms in my sample, including several large airlines such as Delta, US Airways, and Northwest Airlines, as well as large auto parts manufacturers like Dana, Collins & Aikman, and Dura Automotive. Although my specifications always use the natural log of *size*, which diminishes the outsize impact of these outliers, some concern could remain that these "mega" bankruptcies weigh too heavily in my results. To account for this, I first winsorize *size* at the 99$^{th}$ percentile ($744.8 million) before taking the natural log, and re-run my specifications. Winsorizing in this way reduces the mean *size* from $156.7 million to $28.5 million, but only changes the average ln(*size*) from 1.67 to 1.65. This slight change does not affect my results in any significant way.

A second concern is that two bankruptcy districts, Delaware and the Southern District of New York (SDNY), might be altering my results. Delaware and SDNY are well-known as major bankruptcy centers, attracting a disproportionate share of the largest bankruptcy cases (LoPucki, 2005). Because of their focus on Chapter 11 cases, these two districts have extremely low non-business caseloads. In 2003, Delaware's non-business share of caseload was 19%, while SDNY's was 30%. The next lowest was Alaska, with 54% (see Figure 1.4). While my main results include district fixed effects, the concern is that these two districts' exceptionally low non-business caseload share might alter the coefficient estimates of *busy court*, defined as *Post-BAPCPA*-Non-Business Share of Caseload*. The district fixed effect takes care of any constant effect that might be present in these two districts, but any changes that occurred in these two districts after BAPCPA would be magnified by their exceptionally low non-business share of caseload. To account for this, I "winsorize" these two districts by setting their 2003 non-business share of caseload to Alaska's figure of 54%. This affects 321 firms in my sample, or 9.6%. When I alter the non-business share of caseload for Delaware and SDNY in this way, I continue to find that firms that restructure in busy courts are significantly more likely to reorganize, and that large firms are less likely to be converted to Chapter 7 liquidation. Coefficient estimates on the impact of caseload on dismissal are nearly identical in magnitude, but no longer statistically significant. All other results are unchanged or even stronger after adjusting Delaware's and SDNY's non-business caseload share. Also, results that commercial banks located in busier courts experience higher charge-off rates are robust to this altered specification.

Aside from possible issues relating to outliers, an additional concern regarding my results relates to the exclusion restriction: did bankruptcies in consumer-centric districts change in some systematic way after 2005 that is unrelated to court caseload? I address this concern by allowing the time fixed effects to vary across industries, firm sizes, and geographic regions. These more flexible specifications allow me to rule out alternate channels that could be biasing my estimates. For example, if firms of a particular industry tend to be located in bankruptcy districts with high non-business caseload and there was a shift in bankruptcy outcomes for that industry after BAPCPA that is unrelated to the workload of judges, this could bias my estimates of the impact of caseload. Including separate time fixed effects for each industry accounts for these trends, but at the cost of estimating far more coefficients in each model. I find that including industry-by-time fixed effects in this way does not affect my results. Similarly, I also allow the coefficient on ln(*size*) to vary in each quarter and find no difference in the estimates. Lastly, I test whether regional time effects might be driving my results by including separate time fixed effects for each of the nine census divisions: New England, Middle Atlantic, East North Central, West North Central, South Atlantic, East South Central, West South Central, Mountain, and Pacific. These specifications control for the fact that the most consumer-centric bankruptcy districts are concentrated in the South, while the western U.S. tends to be more business-centric (see Figure 1.5). Again, I find the same results in this more flexible specification. For the bank charge-off regressions in Table 1.11, I also run the analysis with separate time fixed effects by bank size and bank region. The results are stronger with the inclusion of these additional controls.[45]

Lastly, in the reported regressions standard errors are clustered either by bankruptcy district (Tables 1.5, 1.7, 1.9, and 1.12) or by commercial bank (Table 1.11). All estimates remain significant if I

[45] The results of these robustness checks are available in the appendix.

double-cluster standard errors both by bankruptcy district (or bank) and time, thereby taking into account mutual dependence within district (or bank) *and* within time period.

## 1.6. Conclusions

This essay has shown that time constraints on bankruptcy judges alter the outcomes of firms that restructure in busy courts. Busy bankruptcy judges are more likely to allow distressed firms to reorganize. This is especially true for larger firms, which are both more complex and better able to lobby bankruptcy judges. I interpret these findings as suggesting that busy judges tend to be more pro-debtor in their decision-making. Firms that are dismissed from busy courts are significantly more likely to re-file for bankruptcy, thereby incurring additional costs of financial distress. Meanwhile, busy courts impose additional costs on reorganizing firms by lengthening bankruptcy stays and increasing the need to sell assets via section 363 auctions. I show that these higher costs of financial distress are borne principally by the creditors of the firm.

While my evidence shows that the costs of financial distress are higher in busy bankruptcy courts, the overall welfare implications are less clear. In particular, it is unclear whether more social value would be created if the marginal firms that are reorganized in busy courts were liquidated instead. In theory, somewhere between the extremes of liquidating all firms or none of them, there is some optimal level of "pro-debtor-ness" for a bankruptcy judge (Aghion et al., 1992; Bernhardt & Nosal, 2004; Gennaioli & Rossi, 2010; Hart, 2000). The location of Chapter 11 on this spectrum remains an open question due to difficulties in finding clean empirical identification, thus making it impossible to determine whether pro-debtor shifts are welfare-reducing or not. However, two recent papers suggest that pro-creditor shifts may enhance firm values. Chang & Schoar (2007) show that Chapter 11 debtors that were randomly assigned to more pro-debtor judges have lower sales and fail at higher rates post-bankruptcy. This suggests that pro-creditor judges enhance the value of firms that survive bankruptcy relative to pro-debtor judges, but it still leaves open the possibility that pro-creditor judges liquidate some firms that would have had more value as going concerns. Becker & Strömberg (2012) examine a Delaware bankruptcy court ruling that shifted corporate directors' fiduciary duties towards creditors. They find that this pro-creditor ruling increased equity values of Delaware firms relative to non-Delaware firms. Taken together, these two papers provide evidence that pro-creditor shifts can enhance firm value. If this is the case, busy bankruptcy courts, which tend to be more pro-debtor, are likely to reduce overall firm value.

This essay uses the passage of BAPCPA as an exogenous shock to bankruptcy caseloads. While this identification allows me to make causal estimates of the impact of changes in court caseload, it ignores knock-on effects that might occur when caseloads change due to general economic conditions. In particular, bankruptcy filings spike during economic recessions, increasing the average annual workload of bankruptcy judges by 32%. Thus, the bankruptcy system is busiest exactly when many firms are trying to restructure. Further, during recessions financially distressed firms have less ability to obtain DIP financing or sell assets at reasonable (not fire sale) prices—actions which would help these firms to handle longer stays in bankruptcy. As these costs are passed on to banks and other creditors, it could also further constrict the credit supply. If bankruptcy is an insurance system that allows firms to work out financial distress in a formal and equitable forum, my results indicate that the insurance system functions worst exactly when financial disasters strike.

This is true both nationwide and on a more local level. It is important to note that court caseloads vary more cross-sectionally than they do over time. While I have couched most of my results in terms of nationwide economic recessions, it is also true that local economic conditions can be quite different across the United States. Localized economic malaise will have the same impact on caseloads in affected bankruptcy districts as nation-wide recessions will. The effects of busy bankruptcy courts matter for not only *when* but also *where* a case is filed.

Overall, my results matter the most for high-beta firms, which are most likely to need bankruptcy protection when courts are busy. Because the legal infrastructure does not adjust to aggregate economic shocks, firms that are most sensitive to those shocks experience higher costs of financial distress, a fact that should be reflected in the costs and structure of their debt.

# 2

# The Ownership and Trading of Debt Claims in Chapter 11 Restructurings

*This chapter is co-authored with Victoria Ivashina and David Smith*

## 2.1. Introduction

Potential bankruptcy costs are widely recognized in corporate finance as one of the key determinants of the choice between debt and equity financing. However, efforts to study these costs empirically have been hampered by data limitations. Furthermore, growing anecdotal evidence suggests that several developments in the financial market—in particular, the emergence of an active market for the trading of bankrupt claims—has dramatically transformed the ownership structure of bankrupt firms and the bankruptcy process with it. Using novel data covering 136 Chapter 11 bankruptcies filed between 1998 and 2009, we study the overall ownership structure of defaulted firms, how this ownership evolves through bankruptcy as a result of the trading of debt claims and, ultimately, how it influences Chapter 11 outcomes.

The level of detail in the data that we put together enables us to overcome some basic measurement problems. Specifically, we directly observe the ownership stakes and identity of virtually all claimholders in the capital structure via two snapshots of holdings recorded during the Chapter 11 proceedings: at the filing of "schedules" of assets and liabilities near the beginning of the case, and at tabulation of votes on the debtor's plan of reorganization.[1] This allows us to compute ownership concentration across the entire capital structure and through bankruptcy, thus, significantly improving measurement over the existing literature, which has relied primarily on the presence of different types of debt to proxy for ownership concentration. In total, we cover 71,358 different investors. Although the court documents only record the names and addresses of these investors, using several data sources, we identify these investors by institutional type. This allows us to further gauge the strategic importance of different investor groups.

Our study is also the first to provide insight into the claims trading that occurs in a bankrupt firm and to show how this trading impacts ownership and, subsequently, bankruptcy outcomes. Specifically, we observe *within* bankruptcy transfers of bilateral claims (trades filed as "Rule 3001(e) proofs of transfer"), which—as we show—is dominated by trade credit.[2] Over the course of the 136 bankruptcy cases, we observe \$1.86 billion of face value traded. Although growth in trading of bankrupt claims has not gone unnoticed (both Gilson (1995) and Baird and Rasmussen (2010) emphasize its potential important for the bankruptcy process), as Levitin (2010) points out, the existing evidence has been only anecdotal.[3] Our study changes that. In that sense, the set of novel facts shown in this essay seeks to be informative to the theoretical literature and to the understanding of the bankruptcy process more broadly.

The findings in this chapter can be summarized as follows: [4]

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[1] Note that the term "bankruptcy claim" is a broader concept than "security," as it includes *any* of the firms' liabilities/right-to-payment. In what follows, we will use indistinctively the terms "claim holders" and "creditors".

[2] Bankruptcy Rule 3001(e) covers the disclosure requirements with respect to bankruptcy claims trading. In 1991 this rule was amended to make clear that it is *not* the court's role to determine the validity of the transfer, unless there is an objection by the transferor. It is often argued that the reduction in court's oversight on claims trading facilitated the development of this market.

[3] "The debate over claims trading (in Chapter 11) operates on a limited evidentiary base. Arguments about claims trading are based on theory, common sense, and anecdote, but not data." (Levitin, 2010.)

[4] In presenting our results, we focus on four key types: (i) banks, (ii) "bond custodians", which include administrative agents, indenture trustees, or financial institution brokers that report debt holdings on behalf of private investors, (iii) non-financial corporations, and (iv) "active investors", which we define to include asset management firms and hedge funds.

While we confirm the importance of bank ownership in the cross-section and throughout the bankruptcy process, we find that non-financial corporations are equally important creditors, accounting for 22.5% of all claims and present in nearly all bankrupt cases. As one would expect, at the onset of bankruptcy, non-financial corporations' holdings are dispersed. However, we show that, through trade, ownership in a substantial fraction of claims held by non-financial corporations is sold, contributing to increased ownership concentration at the time the plan of reorganization is voted upon. Moreover, a large fraction of these claims is purchased by "active" investors, which we define to be hedge funds, private equity funds, and investment management companies. We also establish that active investors hold only 9.8% of debt claims at the onset of bankruptcy, but hedge funds—and active investors more broadly—appear to significantly increase their stake by the stage at which claimants vote on the plan of reorganization, thus accounting for a combined 15.0% of all claims. Their stakes are also concentrated in the voting classes. So, to the degree that hedge funds influence that bankruptcy outcomes they do so with relatively small, but strategic stakes.

We also find that ownership concentration across the capital structure matters for restructuring outcomes. The likelihood of observing a prearranged bankruptcy increases with the concentration of the capital structure, measured at the outset of the bankruptcy case. Subsequently, the bankruptcy process moves more quickly than in cases not filed as a prearranged process.[5] But a concentrated capital structure also improves the speed at which a *non*-prearranged restructuring occurs, and increases the likelihood that a firm reorganizes as an independent entity, as opposed to being sold or liquidated. We also show that the level of debt ownership concentration at the beginning of a bankruptcy case is positively associated with trading in bank loans and bonds prior to the bankruptcy filing, suggesting that trading prior to bankruptcy concentrates the capital structure. To the extent that a quicker bankruptcy, and survival as an independent

[5] Although this result is intuitive, strictly speaking, we cannot establish a causal link between ownership concentration and prearranged filing because our identification is based on trading *during* bankruptcy, whereas the existence of a prearranged reorganization plan is something that is already set at the bankruptcy filing.

going concern are indicators of a more efficient outcome, our results suggest that more concentrated capital structures lead to better restructuring outcomes.

We observe that capital structures with large amounts of claims held by non-financial corporations—a good indicator of high levels of trade credit and other bilateral claims—are less concentrated at the outset of the case, and it is the capital structures of these same firms that become more concentrated through trading during the case. We show that, holding concentration at the start of the case constant, in-bankruptcy ownership consolidation through the trade of bilateral claims is associated with bankruptcy outcomes that are different from those associated with pre-bankruptcy consolidation of ownership. Higher observed in-bankruptcy trading, at the margin, leads to an increased time to the completion of a restructuring, a higher likelihood of the restructuring ending in the liquidation of the firm, and lower aggregate recovery rates. In connection with this last result, we also show that more concentrated classes of creditors receive higher recovery rates, conditional on their seniority in the capital structure. We do not have direct evidence for the underlying mechanism, but our results are consistent with the idea that concentrated classes of creditors are able to bargain for higher recovery rates for themselves, but that this bargaining diminishes the estimated value of the firm at exit. Our results also suggest that the types of investors who enter (and consolidate) the capital structure through in-bankruptcy trading have different objectives than concentrated investors prior to bankruptcy. These results are robust to an instrumental variables approach that uses characteristics of trade credit—a proxy for propensity to trade bilateral claims—to instrument for ownership concentration at bankruptcy exit.

Our essay contributes to a large literature relating capital structure to the cost of financial distress. Gertner and Scharfstein (1991) argue that a major impediment to efficient reorganizations is the inability for dispersed creditors to coordinate bargaining among themselves and with the managers of the bankrupt firm. The underlying assumption in Gertner and Scharfstein (1991) is that the ex-ante capital structure of the distressed firm is fixed, thus, coordination within Chapter 11 can improve efficient bargaining. Likewise, Bolton and Scharfstein (1996) argue that complex capital structures can deter efficient ex-post renegotiation of defaulted contracts, which in turn influences the structure of the ex-ante contract and capital structure of the borrowing firm. Our findings are largely consistent with the inferences in both of these papers, and even can be thought of as a direct test of their implications. However, these studies abstract from the possibility that investors can *trade* to a more concentrated capital structure prior to bargaining, a point that we show is important for understanding distressed negotiations.

On the empirical side, Gilson (1990) and Gilson, John, and Lang (1990) examine restructurings of bank debt during the period 1978-1987 and show that the presence of large bank claims eases the restructuring process, and that banks often end up with a substantial share of equity in the reorganized firm. Asquith, Gertner and Scharfstein (1994), Brown, James, and Mooradian (1993), and James (1995, 1996) extend this work by showing that the impact of bank debt on restructuring depends on the financial condition of the firm and the presence of public debt. As mentioned earlier, our essay significantly improves on the measurement of ownership structure and tracks claim ownership through bankruptcy. We test this statement in a "horse race" comparison of our ownership-concentration measure against the earlier proxies.

More recent studies have focused on the role of strategic investors in distressed debt. Bharath, Panchapegesan, and Werner (2010) and Ayotte and Morrison (2009), show that the speed and efficiency of Chapter 11 restructurings increased significantly from the 1980s through the early 2000s, a period that coincides with both an increase in the sophistication of Chapter 11 players and the development of distressed debt trading markets. But, unlike our essay, neither of these studies observes the identities of the creditors and the extent to which investors affect the Chapter 11 process and outcome. Our essay also relates to Hotchkiss and Mooradian (1997), who examine the role of active investors (defined from a list of 75 distressed debt investors) in distressed companies, and Jiang, Li, and Wang (2012), who track hedge fund participation in firms that file for Chapter 11. These papers find evidence consistent with increases in the efficiency of Chapter 11 outcomes when strategic financial investors are involved. Our findings complement these studies by directly showing that active investors increase their ownership strategically though bankruptcy. However, we also focus on a much broader set of investors—virtually the entire capital structure of the distressed firms—and show that while more concentrated capital structures at the outset of the case appear to improve the efficiency of the restructuring, trading by active investors during the bankruptcy process could contribute to outcomes that are adverse to an efficient restructuring.

The rest of the chapter proceeds as follows. Section 2.2 describes the data. Section 2.3 presents the distribution of institutional debt ownership across the bankrupt firms in our sample and analyzes the observed trading activity in the bankruptcy cases. Section 2.4 analyses effects of ownership concentration on bankruptcy outcomes, and how in-bankruptcy trading affects both concentration and outcomes. Section 2.5 concludes.

## 2.2. Data

To understand the ownership structure of bankrupt claims, we require a complete set of creditors holding claims in a representative sample of U.S. corporations filing for Chapter 11 bankruptcy protection. Because the bulk of debt claims against U.S. companies are unregistered instruments traded over-the-counter, no one reliable source exists for observing the identity and holdings of creditors. Even holders of Securities and Exchange Commission (SEC) registered debt securities, such as publicly traded bonds, are required to identify themselves in only limited circumstances.[6]

To overcome these obstacles, we rely on reports of creditor holdings that are filed during the Chapter 11 bankruptcy process. We obtain our holdings data from the four leading providers of claims administrative services: BMC Group, EPIQ Bankruptcy Solutions, Donlin Recano & Company, and Kurtzman Carson Consultants (KCC). These professional service firms are retained by the debtor to collect, record, and manage claimant databases during the course of the bankruptcy case. In addition to the holdings data, the claims administrators also supply us with information on claims trades that occur during the bankruptcy process. These trades are in a special subset of claims that includes trade claims, lease claims, and other "bilateral claims". (The first section of the Appendix provides a detailed description of the format in which we received the data from the claims administrators.)

[6] Unlike public equity holdings, which require holdings disclosures by all insiders and owners of more than 5% of outstanding shares, public bondholders are typically not required to disclose their holdings or trades. The exceptions to this rule are the bondholdings of insurers, which must be disclosed to the National Association of Insurance Commissioners, and the bondholdings of registered investment managers, which must be disclosed to the SEC.

## TABLE 2.1
## DESCRIPTION OF FIRMS FILING FOR CHAPTER 11 BANKRUPTCY

This table summarizes the characteristics of the 136 firms in our sample that filed for Chapter 11 bankruptcy protection. Panel A reports summary statistics on the filing, evolution, and outcome of the bankruptcies, based on data collected from the *Deal Pipeline* and Chapter 11 disclosure statements. Panel B reports financial characteristics of the sample firms prior to filing for bankruptcy, based on data collected from *Deal Pipeline*, Capital IQ, SDC, and Compustat.

*Panel A: Bankruptcy characteristics (136 filings)*

| Filing year | 1998 | 2000 | 2001 | 2002 | 2003 | 2004 | 2005 | 2006 | 2007 | 2008 | 2009 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Obs. | 1 | 1 | 8 | 13 | 17 | 10 | 16 | 19 | 12 | 32 | 7 |
| | 0.7% | 0.7% | 5.9% | 9.6% | 12.5% | 7.4% | 11.8% | 14.0% | 8.8% | 23.5% | 5.1% |

| Filing court | % Obs. | Filing type | % Obs. |
|---|---|---|---|
| Delaware | 40.4% | Traditional “free-fall” Ch. 11 | 78.4% |
| Southern District NY | 22.1% | Prearranged Ch. 11 | 18.7% |
| Other | 37.5% | Tort-related Ch. 11 | 3.0% |

| | Median | Mean | Std Dev |
|---|---|---|---|
| Time in bankruptcy (days) | 377 | 439.5 | 309.0 |
| Overall recovery rate | | | |
| Value at exit/Liabilities at filing | 50.8% | 54.0% | 51.1% |
| Weighted average claim recoveries | 51.9% | 52.9% | 31.1% |

| Restructuring outcome: | | Claimant group with controlling equity interest at exit, the fulcrum class (reorganizations only): | |
|---|---|---|---|
| Reorganized | 45.2% | DIP Lenders | 8.6% |
| Sold to a financial buyer | 9.7% | Prepetition Lenders | 29.3% |
| Sold to a strategic buyer | 12.7% | Notes/Bondholders | 24.1% |
| Liquidated piecemeal | 32.1% | General Unsecured | 19.0% |
| Identity of owner at exit: | | Subordinated Debt | 3.5% |
| Financial | 64.8% | Equity | 15.5% |
| Strategic | 35.2% | | |

*Panel B: Pre-bankruptcy firm characteristics*

| | Source | Obs. | Mean | Std. Dev. | Median |
|---|---|---|---|---|---|
| Total assets (million $US) | Deal Pipeline | 133 | $1,915.2 | $4,844.7 | $250.4 |
| Revenue (million $US) | Compustat | 64 | $3,858.7 | $13,018.4 | $705.2 |
| Employees | SDC | 71 | 6,731 | 11,780 | 1,994 |
| Cash (million $US) | Capital IQ | 66 | $233.1 | $574.4 | $27.5 |
| Pre-bankruptcy EBITDA (million $US) | Deal Pipeline | 59 | $170.4 | $615.9 | $20.7 |
| Total liabilities (million $US) | Deal Pipeline | 133 | $1,805.4 | $4,299.6 | $372.1 |
| Total liabilities/Total assets | Deal Pipeline | 132 | 3.52 | 18.2 | 1.07 |
| Total liabilities/Total assets (no outliers) | Deal Pipeline | 130 | 1.52 | 1.49 | 1.06 |
| Total debt (million $US) | Capital IQ | 66 | $1,895.1 | $3,686.6 | $393.4 |
| % Bank debt | Capital IQ | 51 | 46.54% | 31.27% | 39.91% |
| % Secured debt | Capital IQ | 55 | 59.16% | 37.89% | 59.05% |
| % Long term debt | Capital IQ | 51 | 66.38% | 35.42% | 84.13% |

Our sample covers a total of 136 relatively large firms that file for Chapter 11 during the period 1998 to 2009. (The full list of bankruptcies in our sample is reported in the Appendix Table B.4.) Bankruptcy and debtor characteristics are summarized in Table 2.1. Our sample is weighted more heavily towards the latter part of our sample period. This is due to the fact that the electronic archiving of data by claims administrators is a relatively new phenomenon.[7] The mean asset size of our sample firms, as reported on the filing of the bankruptcy petition, is over $1.9 billion. But this distribution is skewed; the median firm reports assets of $250 million. The median-sized firm reports liabilities that are slightly larger than assets (1.07 time assets). Meanwhile, the median firm for which we can gather additional financial information enters Chapter 11 reporting $20.7 million in EBITDA and with cash of $27 million on their balance sheets, both indicating that sample firms are filing for bankruptcy financially, but not necessarily economically, distressed.

To gather information on the evolution of each bankruptcy case, we rely primarily on *The Deal Pipeline*'s Bankruptcy Insider archive and the bankruptcy "disclosure statements" filed in court with each debtor's plan of reorganization. Consistent with the practice of many large firms that file for bankruptcy, our sample firms primarily file for Chapter 11 protection in Delaware (40% of cases) and the Southern District of New York in Manhattan (23% of cases). The remaining 37% file in 28 separate courts across U.S. federal court districts. Similar to Bharath, Panchapegesan, and Werner (2012), who show that time in bankruptcy has fallen drastically since the 1990s, the median firm in our sample remain in bankruptcy for just over a year.

We categorize each bankruptcy outcome into one of three categories: (1) a traditional "reorganization," in which a firm exits Chapter 11 intact as free-standing entity with a new capital structure; the new capital structure includes new debt and equity that has been exchanged for the pre-bankruptcy debt claims, (2) a sale of the firm as an independent going-concern to a financial or strategic

[7] For instance, during the period 1998-2003 our sample contains about 10% of the number of large bankruptcies tracked by Lynn Lopucki (http://lopucki.law.ucla.edu/), but 64% of the Lopucki number from 2004-2009. Despite the early-period underrepresentation, the cross-sectional characteristics of our sample as reported in Table 2.1 are very similar to the Lopucki sample.

buyer, typically through a "Section 363" sale, and (3) a liquidation of the firm's assets so that no primary going concern remains at the end of the case; liquidations occur through conversions to Chapter 7, via a Chapter 11 liquidating plan, or through a series of separate Section 363 sales.[8] Just under half (45%) of our sample firms exist via a traditional reorganization. Another 23% are sold as a going concern (10% to financial buyers and 13% to strategic buyers), and 32% are liquidated piecemeal.

Across reorganizations and going-concern sales, financial investors—essentially banks plus hedge funds, private equity sponsors, and other asset management companies—are the dominant controlling owner of firms that emerge from bankruptcy, accounting for ownership of almost two-thirds of the exiting firms. Among reorganizations, the "fulcrum" class of voting claims—that is, the class of claimholders that receives the controlling interest in equity at bankruptcy exit—is most often the class holding senior lender claims (29%), followed by bondholders and noteholders (24%). But, in successful Chapter 11 reorganizations, controlling equity also goes to general unsecured creditors a fair amount of time (19%), as well as the original equity holders (16%). Note that these incidences measure the class that retains control in reorganizations only; across all bankruptcy outcomes, old equity holders exit bankruptcy as the controlling owners in only 7% of the cases.

We calculate firm-level recovery rates two ways: (1) by dividing the estimated enterprise value (in the case of a reorganization) or the total sale proceeds (in the case of a 363 sale or liquidation) by the value of liabilities reported at filing, and (2) by calculating the weighted average recovery rate of the claim classes reported in the bankruptcy case disclosure statement, where the weights correspond to the pre-filing face value of the claims in that class. Both measures produce a similar distribution that shows average and median recovery rates to be around 50% of the original claim values, with standard deviations also of the same order of magnitude.

[8] At times, distinguishing between a going-concern sale and a liquidation can be difficult, as a company may split up into a series of small concerns by division or plant, or may have its sold assets redeployed *in totem* to a strategic buyer, but cease to exist as a separate business. We take the general view that a sale as a going-concern occurs if one part of the business remains as a surviving business entity.

*2.2.1.Claims ownership and trading data*

We observe the holdings of claims against the bankrupt firms in our sample at two points in time. Figure 2.1 provides a timeline representation of when these snapshots are recorded, and the period over which we can observe the trading of claims. The first snapshot occurs at $t_1$, soon after the company files its petition for bankruptcy protection, at the filing of the schedules of assets and liabilities. The second snapshot occurs at $t_2$, the point at which votes from claimants are tabulated for purposes of accepting or rejecting the debtor's plan of reorganization. We also observe trading between $t_1$ and $t_2$ among a subset of claims in the capital structure, a grouping we term "bilateral claims". In the following subsections, we provide more detail on the holdings and trade data.

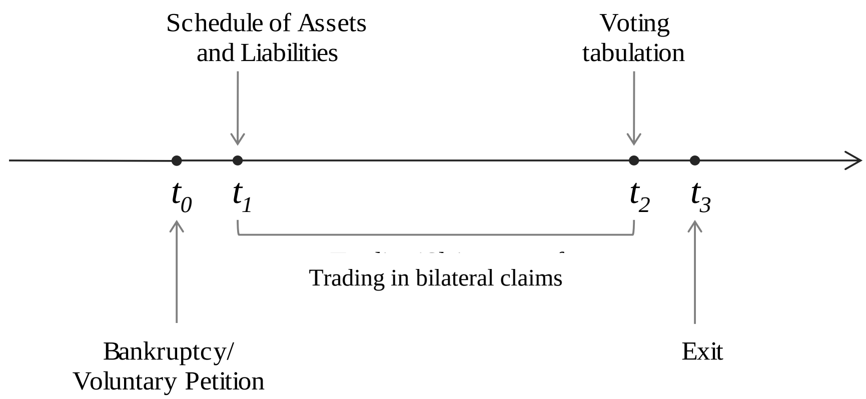


**FIGURE 2.1 – BANKRUPTCY TIMELINE**

*2.2.1.1. Snapshot 1: Schedule of Assets and Liabilities and Credit Register ($t_1$)*

Shortly after entering Chapter 11, the debtor is required to file its "schedules" of assets and liabilities, which—as the name suggests—contain a detailed description of the bankrupt company's assets and liabilities. The description of the debtor's liabilities includes a full listing of all known creditors and other claimants, together with the amount and nature of their claims. Parties missed by the schedules who believe they have a valid claim against the debtor can submit their proof of claim to a central claims register, managed by the claims administrator. Together, the schedules and credit register serve as a record of each asserted claim, including the amount of the claim, type of claim, and the name and address of the claimholder, as of the start of the bankruptcy case. For ease of exposition, we denote the point in time at which the filing of the schedules and claims register occurs as $t_1$.

There is one group of investors whose identifies we cannot observe directly from the schedules and register: investors in bonds and notes held through the Depository Trust & Clearing Corporation (DTCC). This group, which comprises holders of most SEC-registered bonds and notes, stands behind a curtain of DTCC members and participants, who play a custodial role in reporting holdings on behalf of the beneficial holders.[9] The original holders of these claims are nearly impossible to identify directly. In their place, we observe the identity of the custodian, which is often a large financial institution. As discussed below, we use a variety of techniques to separate custodial bond holdings reported by financial institutions from the direct holdings of bankrupt claims by financial institutions. This enables to distinguish bond and note holdings from other financial claims, and to measure the influence of the censoring of these observations on our results.

#### *2.2.1.2. Snapshot 2: Plan vote tabulations ($t_2$)*

An important part of a bankruptcy restructuring is the plan of reorganization, which details how a bankrupt firm plans to restructure its operations and capital structure, and exit bankruptcy as a viable entity. In order for this plan to be confirmed by the bankruptcy judge, the plan must be approved by all claimant classes that are entitled to vote for the plan. Voting for the plan takes place via a balloting agent, which is often one of the four claims administrators providing us with data. Our second snapshot comes from the record of the votes by all claimants entitled to vote. The tabulations include the identity of the voting claimant, the number of claims being voted, the amount of the claim, and the vote to approve or reject the plan.[10] As shown in Figure 2.1, we denote the point in time when votes are tabulated as $t_2$.

[9] In fact, to reach out to bondholders for the purposes of collecting holder specific votes, the DTCC sends out a master ballot to DTCC member institutions which hold interests in the DTCC note on behalf of broker/dealers who act as "prime brokers" to the beneficial holders, and in turn hold the interests on behalf of the beneficial holder. Reporting on behalf of the beneficial holder feeds back through the prime broker to the DTCC member, who then reports directly to the claims administration service for purpose of recording holdings in the schedules and votes at tabulation. We thank one of our referees for clarifying this process.

[10] Several plans for reorganization of the failed company can be submitted. With each plan, the court must approve the disclosure statement before a vote is cast. If the vote fails, the plan can be crammed down, but often it is

From a data quality perspective, the vote tabulations are superior to the schedules and register in two important ways. First, vote tabulations are clean of errors and duplication. Only creditors certified by the judge as valid, or "allowed" in bankruptcy parlance, are permitted to vote. All duplicate, false, and disallowed claims that could appear in the schedules and register are eliminated at the time of the vote.[11] Second, because the vote tabulations are grouped according to creditor class, we gain specific information on the type and priority of claims held by voting claimants. This level of detail is unavailable at the filing of the schedules. As in the case of the holdings reported at the schedules and register, we cannot identify the beneficial owner of the debt for DTCC notes and bonds.

Not all allowed claimants are entitled to vote on the plan of reorganization. Claimants unimpaired under the plan, i.e., those that will receive 100% of the value of their original claim at the end of the case, are deemed automatically to accept the plan and do not vote. In addition, impaired claimants that receive no recovery under the plan, i.e., those claims and equity interests that are "out of the money" according to the plan valuation, are deemed automatically to reject the plan and are excluded from voting. Classes entitled to vote are impaired claimants that receive a nonzero distribution under the plan. These are the classes for which we observe holdings at $t_2$. Figure 2.2 illustrates how the snapshots of the capital structure differ between $t_1$ and $t_2$.[12]

#### 2.2.1.3. *Observed claims trading between $t_1$ and $t_2$*

In addition to the data observed in these two snapshots, we also observe trading in a subset of the claims in our sample. The subset consists of all claims that are required to submit proofs of transfer under Rule 3001(e) of the Federal Rules of Bankruptcy Procedure whenever the claims are traded ("assigned") during the bankruptcy case. According to Rule 3001(e), any traded bankruptcy claim that is not "based

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converted to the Chapter 7 liquidation. So, for each case there is only one vote and one point in time when the votes are tabulated.

[11] We have carefully searched for duplicate and disallowed claims in the $t_1$ data using flags in the data that denote denied claims, computer algorithms that identify probable duplicate claims, and identifying large duplicate claims by hand. Even so, we cannot be sure that we have removed all invalid claims.

[12] Often, senior secured classes will be deemed impaired and get a vote even though they are expected to receive a 100% recovery. They are deemed impaired when they may not receive their distribution immediately following the exit, and instead they may receive new debt claims with different terms than their original debt.

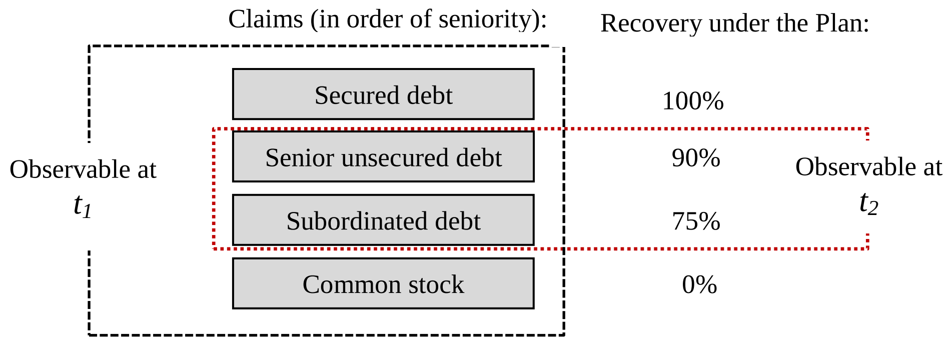


**FIGURE 2.2 - EXAMPLE OF DATA AVAILABILITY AT $t_1$ AND $t_2$**

on a publicly traded note, bond, or debenture" is required to file proof of the transfer with the court. In practice, trades in syndicated bank loans are also excluded from Rule 3001(e) because the trades are tracked by the administrative agent on the loan. Beyond public debt securities and bank loans, all other claims against the debtor that trade during the case are required to file a 3001(e) proof of transfer. These include all trade and vendor claims, derivative instruments and swaps, intercompany claims, rejected lease and lease cure claims, and tax claims. The filed proof of transfer includes the identity of the claim, the seller, and the buyer, as well as the asserted face value of the claim. For convenience, we refer to claims reporting under Rule 3001(e) as "bilateral claims" because trades occur directly between the buyer and seller without a third-party agent or custodian.

The bulk of bilateral claims are traded *during* the bankruptcy case, so our data captures most (if not all) of the bilateral claims transfers. This is because holders of bilateral claims are hard to identify and locate prior to the filing of the schedules of assets and liabilities. Furthermore, the individual holdings tend to be relatively small. The schedules (and claims register) are the primary source that claims traders use to locate potential sellers.

We use the bilateral claims trade data to draw connections between claims trading in bankruptcy and changes in the ownership and concentration between $t_1$ and $t_2$. All claims within a class are treated exactly the same from the perspective of the plan of reorganization, regardless of whether they are bilateral or not. Thus, general interest in a firm's bilateral claims should signal interest in other claims of the same priority in the capital structure, since such claims receive the same recovery and have the same creditor rights. Furthermore, bilateral claims are typically general unsecured claims that lie in the "middle" of the capital structure; they are often impaired but entitled to some distribution under the plan, so they fall within the group of classes entitled to vote (we will confirm this in the data).

The negotiation and subsequent vote on the reorganization plan is one of the central mechanisms for influencing the course of bankruptcy. So if there is strategic trading—that is, trading with the intention of influencing the bankruptcy outcome—it is likely to be in claims of the same priority as bilateral claims, including bilateral claims themselves. That said, anecdotal evidence from market participants, as well as regression results that we present below, suggest that substantial strategic trading in the capital structure of a bankrupt firm takes place prior to the Chapter 11 filing, in loan and bond claims. Even during the case, large positions in bilateral claims are also costly to amass due to the dispersed nature of the claims and lack of standardized trading practices. Because of this, the observed trading volume of bilateral claims should be thought of as the lower bound for the overall trading volume in bankruptcy claims.

There is an additional point that one should keep in mind. The reorganization plan—the payoff to different classes of claimholders—is structured to be approved and, in this sense, it is endogenous. To avoid prolonged bargaining more senior classes could agree to payment in violation of absolute priority to the concentrated junior classes. So we look at concentration at $t_2$ we only capture the effects of trade on consolidation of ownership in voting classes, and miss those classes that are paid at par as the result of concentration. To the degree that this is true, we could be understating the importance of trading in bankruptcy.

*2.2.2. Identifying and categorizing creditor types*

Our initial sample, compiled from the four claims administration firms, contains a total of 1,461,967 claims across the 136 bankruptcies in our study. Before attempting to identify the institutional type of each creditor, we first reduce the data to a more manageable size by excluding all claims of less than \$50,000, most of which are held by individuals, or are small trade and tax claims. This restriction reduces the sample of claims to 122,530, but on a value-weighted basis amounts to a loss of only 2.4% of the original sample. The sample is further reduced by eliminating, to as great extent as possible, all entries of duplicate and erroneous claims. This results in a final database of 79,527 claims held by 71,358 unique creditors at $t_1$ or $t_2$.

Among the 71,358 unique creditors, we are able to identify 96.8% by institutional type, representing 98.3% of the total value of claims. We categorize creditors by matching their names to descriptions provided by Standard and Poor's Capital IQ database, as well as other data sources, such as the BarclayHedge database of hedge fund managers, and The Deal Pipeline. We employ a variety of electronic text search and matching algorithms to aid in linking the creditor names to institutions, but all matches are checked by hand for accuracy. For each matched creditor name, we create a parent identifier and assign a parent institutional type to the creditor record. At the parent level, we identify thirteen institutional types, but in presenting most of our results, we focus on four key institutional types: (i) "banks", including commercial and investment banks, and their subsidiaries; (ii) "bond custodians," which are institutions reporting on behalf of the beneficial holders of bonds and notes, (iii) "non-financial corporations", and (iv) "active investors", which is subcategorized into hedge fund holdings and asset management holdings.[13] The first column of Table 2.2 contains a complete list of the 13 institutional investors.

Note that the bond custodian category is the only grouping of holdings in which we do not observe the identity of the actual holder of the claims. At the filing of the schedules, we identify custodians by (1) name, for example, holdings reported by Bank of New York or State Street Bank are almost always custodial holdings; (2) searching for institutions identified as a "trustee" or "agent" in the claimant name field, for example, "J.P. Morgan as trustee"; (3) examining bankruptcy disclosure statements, which often identify trustees, custodians, and agents as part of the disclosure; (4) flagging institutions that report voting for more than once investor in the vote tabulation.

[13] Following Jiang, Li, and Wang (2012), we count private equity (PE) sponsors as hedge funds. We identify 90 different investors under "hedge funds" across the 136 cases at $t_1$ and 74 different hedge funds across the 116 vote tabulations at $t_2$. By comparison, Jiang, Li, and Wang (2012) identify 484 unique hedge funds across their sample of 474 bankruptcies.

## TABLE 2.2

## DISTRIBUTION OF CLAIM OWNERSHIP BY INSTITUTIONAL TYPE

This table reports the distribution of Chapter 11 claim ownership sorted by the institutional type of the claimholder at two points in time: The filing of the Schedule of Assets and Liabilities ($t_1$) and at the tabulation of votes on a Plan of Reorganization ($t_2$). We measure institutional type at the parent level. All numbers are value-weighted. The level of creditor concentration is measured using a dollar-weighted Herfindahl-Hirschman Index (HHI), with a maximum of one. Panel A reports the distribution of ownership across the sample of 136 debtor firms, where an absent institutional type receives a zero weight in the calculation. Panel B shows how ownership by different institutional types varies *within* a given type of credit claim (secured, unsecured, etc.). Panel C reports how ownership by a given institutional type is distributed *across* identified types of credit in the capital structure. Identification of credit types at $t_2$ comes from description of credit classes described contained in the plan of reorganization. The class of general unsecured claims often contains notes and trade claims, while in some cases these classes separated out from other unsecured claims and can thus be identified separately.

*Panel A: General distribution by institutional type*

| | At filing of Schedule of Assets and Liabilities ($t_1$), all creditors | | | | | | At vote tabulation ($t_2$), voting creditors only | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Creditor institutional type: | Cases involving ownership of given institutional type (%) | Mean (%) | Std. Dev. (%) | Median (%) | $95^{th}$ % | HHI Concentration (0 to 1) | Cases involving ownership of given institutional type (%) | Mean (%) | Std. Dev. (%) | Median (%) | $95^{th}$ % | HHI Concentration (0 to 1) |
| Banks | 88.72 | 21.65 | 24.75 | 13.52 | 76.46 | 0.67 | 72.41 | 21.69 | 27.29 | 10.73 | 82.86 | 0.56 |
| Corporations | 96.99 | 22.47 | 22.14 | 14.57 | 71.84 | 0.28 | 94.83 | 24.07 | 25.99 | 17.20 | 90.56 | 0.42 |
| Bonds custodians | 44.36 | 12.25 | 21.99 | 0.00 | 62.56 | 0.84 | 39.66 | 5.92 | 15.07 | 0.00 | 33.27 | 0.85 |
| Active investors: | 76.69 | 9.80 | 21.28 | 0.45 | 69.32 | 0.68 | 76.72 | 14.95 | 23.43 | 2.82 | 81.21 | 0.64 |
| Asset managers | 64.66 | 6.97 | 17.86 | 0.13 | 47.05 | 0.71 | 62.93 | 9.10 | 17.66 | 0.86 | 47.65 | 0.66 |
| Hedge funds | 42.86 | 2.83 | 12.44 | 0.00 | 16.56 | 0.71 | 51.72 | 5.85 | 16.60 | 0.07 | 37.01 | 0.74 |
| Sub-total: | -- | 66.17 | -- | -- | -- | -- | -- | 66.64 | -- | -- | -- | -- |
| The following investor categories are dropped from the later tables. | | | | | | | | | | | | |
| Other financial creditors: | | | | | | | | | | | | |
| Insurance | 63.91 | 1.98 | 8.81 | 0.04 | 6.90 | 0.72 | 34.48 | 1.89 | 7.87 | 0.00 | 10.87 | 0.75 |
| Real estate | 64.66 | 1.47 | 3.49 | 0.05 | 7.67 | 0.62 | 31.90 | 1.06 | 3.45 | 0.00 | 5.41 | 0.78 |
| Other financial | 42.11 | 1.54 | 6.24 | 0.00 | 8.59 | 0.75 | 22.41 | 1.78 | 10.07 | 0.00 | 5.70 | 0.91 |
| Potentially financial | 94.74 | 3.57 | 6.89 | 1.08 | 16.53 | 0.32 | 87.07 | 7.53 | 11.58 | 1.91 | 32.29 | 0.46 |
| Other non-financial creditors: | | | | | | | | | | | | |
| Government | 87.22 | 5.53 | 11.25 | 1.37 | 18.98 | 0.54 | 39.66 | 4.36 | 14.81 | 0.00 | 39.24 | 0.80 |
| Person | 93.23 | 11.57 | 18.82 | 3.48 | 60.24 | 0.33 | 82.76 | 12.21 | 22.46 | 2.39 | 73.52 | 0.44 |
| Intra-company | 36.09 | 4.60 | 10.28 | 0.00 | 25.45 | 0.80 | 12.07 | 2.19 | 9.80 | 0.00 | 20.04 | 0.82 |
| Unknown | 89.47 | 3.57 | 8.38 | 0.55 | 24.03 | 0.47 | 65.52 | 2.34 | 6.42 | 0.09 | 12.33 | 0.59 |
| Total: | -- | 100 | -- | -- | -- | -- | -- | 100 | -- | -- | -- | -- |

## TABLE 2.2 – *continued*

*Panel B: Creditors' ownership by credit class*

| Creditor institutional type: | At filing of Schedule of Assets and Liabilities ($t_1$), all creditors | | | | At votes tabulation ($t_2$), voting creditors only | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Secured | Unsecured | Other | Total: | Loans | Senior notes | General unsecured claims | Trade claims | Employee/ Pension | Tort | Equity | Other | Total: |
| Banks | 43.39 | 52.94 | 3.66 | 100 | 38.62 | 16.19 | 42.32 | 0.61 | 0.00 | 0.00 | 1.07 | 1.19 | 100 |
| Corporations | 9.50 | 84.76 | 5.74 | 100 | 13.72 | 5.80 | 69.51 | 3.61 | 0.68 | 3.91 | 2.51 | 0.27 | 100 |
| Bond custodians | 21.00 | 74.55 | 4.45 | 100 | 24.07 | 31.20 | 37.85 | 2.17 | 0.00 | 2.17 | 2.53 | 0.00 | 100 |
| Active investors: | | | | | | | | | | | | | |
| Asset managers | 17.75 | 76.80 | 5.45 | 100 | 36.65 | 10.76 | 47.36 | 0.62 | 1.37 | 1.37 | 1.87 | 0.00 | 100 |
| Hedge funds | 11.03 | 84.77 | 4.20 | 100 | 35.19 | 9.34 | 53.29 | 1.68 | 0.00 | 0.00 | 0.00 | 0.50 | 100 |

*Panel C: Distribution of creditors within credit class*

| | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Banks | 42.91 | 11.70 | 4.45 | -- | 34.52 | 39.20 | 12.96 | 15.37 | 0.00 | 0.00 | 13.45 | 4.55 | -- |
| Corporations | 16.69 | 29.77 | 19.50 | -- | 17.64 | 6.15 | 38.92 | 58.40 | 4.92 | 32.01 | 34.74 | 18.67 | -- |
| Bond custodians | 9.01 | 13.69 | 3.00 | -- | 1.58 | 17.32 | 4.01 | 0.03 | 0.00 | 3.40 | 20.87 | 0.00 | -- |
| Active investors: | | | | | | | | | | | | | |
| Asset managers | 7.93 | 6.11 | 2.42 | -- | 12.91 | 3.63 | 5.73 | 0.28 | 12.50 | 0.22 | 4.08 | 0.00 | -- |
| Hedge funds | 1.75 | 2.28 | 0.46 | -- | 8.46 | 4.49 | 2.98 | 1.73 | 0.00 | 0.00 | 0.00 | 4.14 | -- |
| Total: | 78.29 | 63.55 | 29.82 | | 75.12 | 70.79 | 64.61 | 75.81 | 17.42 | 35.63 | 73.13 | 27.36 | |

## 2.3. Firm Ownership through the Bankruptcy

### *2.3.1. Ownership concentration at bankruptcy and beyond*

The goal of this essay is to understand the distribution of debt ownership in bankrupt firms, how trading impacts ownership concentration, and, ultimately, how ownership concentration and trading relate to the evolution of the bankruptcy restructuring. We start in Table 2.2 by analyzing the distribution of claims ownership at $t_1$ and $t_2$, across institutional types and the capital structure of the bankrupt firms.

The first observation to emerge from Panel A of Table 2.2 is that banks are a substantial and concentrated holder of bankrupt claims throughout the bankruptcy case. At the onset of bankruptcy, they are present in 88.9% of the cases (Column 1) and own an average of 21.7% of the claims in the sample firms (Column 2). (Conditional on at least one bank holding claims at bankruptcy, banks account for 21.7% / 88.7% = 24.5% of the ownership of Chapter 11 claims in a bankrupt firm). At the time of the plan vote tabulation, banks hold a similar stake of the voting claims. As measured by the Herfindahl-Hirschman Index (HHI), bank ownership is also highly concentrated, both at $t_1$ (Column 6) and at $t_2$ (Column 12). Overall, these findings are supportive of earlier studies—such as Gilson (1990) and Gilson, John, and Lang (1990)—that argue that the presence of banks proxies for a more concentrated set of creditors in the capital structure.[14]

What has been missed by the existing literature is the fact that non-financial corporations represent at least as much as of the capital structure of the bankrupt firms as loans or bonds. In our sample, non-financial corporations are present in nearly all cases and account for an average of 22.5% (median of 14.6%) of the claims of the sample firms. A large portion of claims held by non-financial corporations are in the form of trade credit and related claims for services and products purchased by the

[14] Also consistent with the assumptions in the literature, bond custodians on average hold 27.6% of the bankrupt claims, conditional on being present in the capital structure. However, at $t_1$, "bond custodians" also captures some syndicated loans holdings because agent banks will sometimes report holdings for the entire syndicate. At $t_2$, owners of syndicate claims vote on their own behalf (rather than through the agent bank) and subsequently show up in their institutional grouping. This is likely explanation for the big drop in bond custodian holdings at $t_2$.

bankrupt firm.[15] Indeed, the observed average 22.5% of claims owned by non-financial corporations corresponds closely to the findings in Rajan and Zingales (1995), who show that trade credit represents 22.8% of the liabilities of private U.S. firms. Compared to banks, ownership concentration within the group of non-financial corporations is dispersed, which could justify it is exclusion from the analysis of ownership concentration in previous studies. However, as we will show in in the next section, claims held by non-financial corporations make up a substantial fraction of the bilateral claims purchased in bankruptcy, which concentrates these claims between $t_1$ and $t_2$.[16] Given that all claims can be traded in bankruptcy, large blocks of ownership—like claims held by non-financial corporations—become pivotal to understanding the ownership of a bankrupt firm, regardless of the concentration of these holdings at the start of the case.

The recent study by Jiang, Li, and Wang (2012) emphasizes the role that active investors play in Chapter 11 restructurings, and argues that active investors participate in some fashion in 87% of all large bankruptcy cases. Consistent with their study, the overall *incidence* of active investors in our sample is high. Roughly 77% of firms filing for Chapter 11 have an active investor holding some of the claims throughout the bankruptcy process, and 60% of the cases have a hedge fund positively identified at either the filing of schedules, the vote tabulation, or at both points. However, we find that at the onset of bankruptcy, active investors hold only 9.8% of the claims (12.8% conditional on cases where active investors are present), and hedge funds account for specifically 2.8% of the all holdings (6.5% conditional

[15] For example, for Kmart the largest claimants classified as corporations are: Fleming Companies, a food distributor; D&J Limited Partnership, a clothing manufacturer; Handleman, a media distributor; Universal Music and Video, another media distributor; Premier Retail Networks, a marketing firm. For Pierre Foods, a prepackaged food producer, largest corporate claims are: Zartic, a meat processor; Clovervale farms, food producer; Chef's Pantry, another food producer; Interstate Warehousing, refrigerating warehousing firm; Archer Daniels Midland, food distributor and merchandiser. We also mapped firms classified as Corporations to Compustat. Using this mapping we are able to compare the industry distribution of trade partners in our sample to input-output tables (www.bea.gov/industry/) that provides information on the flow of goods and services that make up the production processes of industries. Industry distribution of claims held by Corporations in our sample is very close to the BEA data.

[16] Although the average holding of non-financial corporations between $t_1$ and $t_2$ does not change much, we must keep in mind that these fractions have different denominators (all claims vs. voting claims). So for claims concentrated in voting classes, like the holdings of non-financial corporations, this seeming lack of change actually entails a significant drop in ownership.

on cases where hedge funds are present). The distribution of hedge funds ownership is highly skewed, such that for the five cases with the largest hedge fund ownership at the filing for bankruptcy, the average holding at $t_1$ is 54.4%, while the remainder of the cases has very little hedge fund ownership.

What stands out is that hedge funds—and active investors more broadly—appear to significantly increase their involvement by the time claimants vote on the plan of reorganization. Conditional on hedge fund presence, their ownership at $t_2$ is more than double of that at $t_1$. Part of the observed increase arises mechanically from loan holdings that were hidden at $t_1$ behind an agent bank. But, as we show in Section 2.3.2 below, active investors play a significant role in the purchases of bankruptcy claims during the case, which increases their stake in bankrupt firms over the course of the bankruptcy.

Active investors are also strategically positioned in the capital structure of bankrupt firms. For instance, among the subset of firms that reorganize in Chapter 11 and report tabulations, active investors are present in 76% of the fulcrum classes (the classes which convert to the largest ownership stake in the reorganized firm). When active investors are present in the fulcrum class, they own an average of 32% of the entire class, close to the strategically important 1/3 required to block approval of a plan of reorganization.[17] So, to the degree that hedge funds assert their power in bankruptcy, they do so with relatively small, but strategic stakes. This stresses the importance of trading in distress claims (including transfer of claims in bankruptcy) for the evolution of the bankruptcy process.[18]

Panels B and C of Table 2.2 provide insight into the types of claims held by the different institutional groups. At $t_1$, we observe only a coarse division into secured claims, unsecured claims, and "other" claims, which include unpaid wages and taxes, and administrative claims. At $t_2$, we observe a finer breakdown by classes entitled to vote, including loans, senior notes, a catch-all class of "general

[17] In 64% of the cases, we observe holders identified specifically as hedge funds, on average, they hold 24% of the fulcrum amount when they are present in the class.

[18] From the claims data we do not observer the extent to which claimholders play important roles in the Chapter 11 process outside of acquiring, holding, and voting the claims themselves. One concern therefore is that the fate of the Chapter 11 restructuring is swayed by strategic players that are not claimholders and therefore stand outside of our sample. In the Appendix, Table B.5, we evaluate this statement by looking at the frequency with which investors in our claims data also act as players in relevant financing and control events that occur during the Chapter 11 case, and find that our approach captures a significant fraction of those cases.

unsecured claims" ("GUCs"), and specific classes—used from time to time—of bilateral claims for trade, tort, and employee/pension claims. The specific bilateral claims classes should be interpreted cautiously because, for the bulk of the bankruptcy cases, these claims are not segregated out from the GUCs class. We also observe holdings by investors in a firm's "old" equity when equity interests are entitled to vote, i.e., when there is enough estimated value in the assets for there to be some residual for the firm's original equityholders.

Panel B reports the distribution of claim holdings by institutional type *across* claims, and Panel C reports the distribution of claims held by each institutional type *within* a particular claim. Panel B shows that, on a value-weighted basis, unsecured claims dominate the portfolios of the main institutional types at $t_1$, including banks. The predominant holdings at $t_2$ are GUCs, where most bilateral claims reside. This is particularly the case for non-financial corporations, which hold 69.5% of their claims in the form of GUCs. Note that on a value-weighted basis, holdings in the classes of old equity interests are relatively small.

Panel C shows that, in line with their role as senior secured lenders, banks are the dominant holders of secured claims (42.9%) at $t_1$ and the largest holder of loan claims (34.5%) at $t_2$. But banks are also substantial owners of senior unsecured notes (39.2%), and they take nontrivial positions in GUCs (13.0%), trade claims (15.4%), and equity (13.5%), although as noted above, Panel B indicates that these equity positions are small on a value-weighted basis. Non-loan claims owned by banks are held primarily through their proprietary trading desks and subsidiary investment funds, and could reflect distressed debt purchases by these subsidiaries. Consistent with the interpretation that they are predominantly trade claimants, non-financial corporations hold the largest stakes in GUCs (38.9%) and trade claims (58.4%). But non-financial corporations also hold a substantial portion of the equity that gets to vote (34.7%). Bond custodial holdings are more often unsecured and represent significant positions in senior unsecured notes (17.3%) and equity (20.3%). Active investors split their holdings evenly across both secured and unsecured claims, holding 21.4% of all loan claims, 12.5% of employee/pension claims, 8.1% of senior notes, and 8.7% of GUCs. Active investors hold very little (4.1%) of the equity available for voting.

An important takeaway from Panels B and C is that holdings by institutional types cluster in the "top" (secured claims and loans) and "middle" (senior notes and GUCs) of the priority structure of bankrupt firms. It is in these areas of the capital structure, where much of the value of the company remains, that most of the restructuring negotiations and battles take place. One of the advantages of our study is that we observe trading in the strategically important middle region of the capital structure during the time between $t_1$ and $t_2$. We now turn to examining this trading more closely.

*2.3.2. Claims trading during Chapter 11*

As mentioned earlier, our data contains in-bankruptcy transfers of bilateral claims. While nearly all institutional types own some amount of bilateral claims, a large fraction of these claims are held by non-financial corporations, which we have shown to be economically important and concentrated within strategically relevant voting classes in in the middle of the capital structure. We should also reemphasize that within a given class all claims are treated the same under the reorganization plan. So while transfers of bilateral claims are a subset of trading in bankruptcy, they are likely a representative subset of trading in strategic classes during the bankruptcy case. However, in examining the trade behavior, two caveats are in order. First, the trading we observe takes place during the bankruptcy case, between $t_1$ and $t_2$, and much of the strategic trading in the capital structure of a financially distressed firm is likely to takes place before the bankruptcy filing. Second, as discussed in Section 2.3, the costs of acquiring bilateral claims is likely higher than the costs of purchasing loans or bonds.

Table 2.3 summarizes patterns in claims trading across institutional types. Panel A reports the value-weighted proportion of total claims traded that are bought and sold by each institutional type. The first three columns look at the full sample. We then examine these numbers on a mean basis across the sample firms. The first thing to note is that active investors (asset management firms and hedge funds) are large buyers of claims in bankruptcy. These investors are the buyers in 38% of all bilateral claims that are

## TABLE 2.3

### ANALYSIS OF CLAIMS TRADING IN BANKRUPTCY

The focus of this table is on the trade of bilateral creditor claims observed *after* the bankruptcy filing but before the voting on the plan of reorganization. In Panel A, the first three columns report the institutional type of buyers and sellers as a percentage of all transfers (value-weighted). To compute these numbers we condition the sample on those cases in which we have record of at least one transfer. In the "who sells" and "who buys" analysis, the mean corresponds to the unconditional mean, that is, we use zeros if there is no sell or buy information for a given type. For example, if in the typical case $100 of claims were traded, we would expect $7.11 of those to be sold by banks, and $61.12 sold by corporations. Conditional means (conditional on a given institutional type engaging in trading) can be easily computed using percentage of cases with seller/buyer of a given type. Panel B separates trades by institutional types into claims that are eventually used to vote on a plan, and those claims that are non-voting. This panel uses a subset of 36 bankruptcies for which we observe trading and can unambiguously link claims between the register and voting tabulations. All figures are value-weighted.

*Panel A: Claims trading by institutional type*

| | | | | Who sells: | | | Who buys: | | |
|---|---|---|---|---|---|---|---|---|---|
| Creditor institutional type: | % of all sellers | % of all buyers | % of all net buyers | % of cases with seller of type | Mean (%) | Std.Dev. (%) | % of cases with buyer of type | Mean (%) | Std.Dev. (%) |
| Banks | 41.41 | 41.41 | 0.01 | 23.94 | 7.11 | 21.24 | 21.13 | 9.08 | 25.36 |
| Corporations | 34.49 | 3.71 | -30.78 | 85.92 | 61.12 | 38.49 | 35.21 | 10.43 | 25.44 |
| Bonds custodians | 7.37 | 1.83 | -5.54 | 4.23 | 0.94 | 7.41 | 8.45 | 2.23 | 10.95 |
| Active investors: | | | | | | | | | |
| Asset managers | 1.06 | 17.73 | 16.67 | 14.08 | 3.07 | 16.52 | 39.44 | 13.02 | 27.93 |
| Hedge funds | 0.21 | 20.06 | 19.84 | 15.49 | 0.97 | 4.97 | 73.24 | 42.35 | 38.19 |
| Total: | 84.54 | 84.74 | 0.20 | -- | 73.21 | -- | -- | 77.10 | -- |

*Panel B: Claims trading by class (BMC cases only)*

| | Non-voting claims: | | | Voting claims: | | |
|---|---|---|---|---|---|---|
| Creditor institutional type: | % of all sellers | % of all buyers | % of all net buyers | % of all sellers | % of all buyers | % of all net buyers |
| Banks | 6.60 | 9.53 | 2.92 | 0.00 | 19.12 | 19.12 |
| Corporations | 65.82 | 8.76 | -57.06 | 70.32 | 0.38 | -69.94 |
| Bonds custodians | 0.97 | 0.79 | -0.18 | 0.00 | 0.00 | 0.00 |
| Active investors: | | | | | | |
| Asset managers | 0.47 | 26.59 | 26.12 | 0.00 | 29.88 | 29.88 |
| Hedge funds | 0.19 | 28.62 | 28.43 | 0.66 | 40.04 | 39.37 |
| Total: | 74.04 | 74.28 | 0.24 | 70.99 | 89.42 | 18.43 |

traded and sellers in almost none of the trades; they also engage in buying claims in a staggering 73% of the bankruptcy cases. Although the selling of claims should be interpreted cautiously since only institutions that own bilateral claims can sell them, it is unlikely that active investors are selling their other holdings while buying claims from corporations. This means that overall holdings of the active investors increase through bankruptcy. The second important finding is that non-financial corporations are important net sellers of bilateral claims, representing 34.5% of all bilateral claims sold and only 3.8% of claims acquired during the cases. Corporations appear as sellers in 86% of the bankruptcy cases. In unreported results we directly track how claims transfer across institutional types and show that active investors are the largest buyers of claims held by non-financial corporations. Specifically, we find that 42.6% of claims held by non-financial corporations that end up being sold are purchased by active investors. (The second largest buyer is banks with 25.2% purchased from corporations.)

While non-financial corporations appear as sellers in nearly all cases, much of the observed trading is concentrated in a small number of cases. For example, on average across our sample, 5.2% of all claims held by corporations are sold during bankruptcy, but in the top ten most actively traded cases, an average of 23% of all corporate claims are sold. This skewed pattern is consistent with observed trading overall, in which we see some trading in many cases, but significant amounts of trading in a smaller number.[19]

Banks proprietary trading desks often facilitate markets making for bilateral claims. As a result, banks are large buyers and sellers of bilateral claims, exchanging roughly 41% of all claims, but taking a net zero position. Meanwhile, bond custodians are also shown as net sellers, albeit in relatively small amounts. A sale (purchase) by a bond custodian implies that the buyer elects to identify (hide) himself directly as beneficial holder. Bond custodian sales account for 7.4% of all sales and 1.8% of purchases.

[19] It should be noted, however, that it is not necessary to purchase a large overall share of the capital structure to influence the outcome of a bankruptcy case. For example, owning a 33% of just one voting class gives a creditor a blocking position which could potentially hold up the entire plan of reorganization.

For the 36 bankruptcies administered by the claims administrator BMC Group, there is an extensive accounting of the Chapter 11 claims, from the time they are entered in the schedules or register through to the time of the vote tabulation. This detailed record-keeping allows us to track whether traded claims are eventually entitled to vote on the plan of reorganization; in other words, we can check whether trading volume is higher in claims that have strategic importance to the vote on the plan of reorganization. The results are reported in in Panel B of Table 2.3. We find that a disproportionally large amount of traded claims are for voting purposes. A traded claim is roughly 38% more likely to be a voting claim than a non-voting claim. Weighted by the face value of the claim, claims that are entitled to vote are more than two and a half times more likely to trade than a claim that does not vote.[20]

In Panel B of Table 2.3, we can also see that banks and active investors (particularly hedge funds) account for a substantially larger portion of net purchases of voting claims than non-voting claims. Combined, banks and active investors comprise 88.4% of all net purchases of voting claims, but 57.4% of all net buyers of non-voting claims. (Although, a large fraction of traded claims is non-voting, and based on some anecdotal accounts this might be endogenous. Claims are paid at par, so they do not get to vote, and do not get equity in the restructured firm.) This suggests that purchases of Chapter 11 claims by banks and active investors are strategic in the sense that they concentrate on claims that will allow them to influence the voting on the reorganization plan.

An additional interesting fact is trade timing is bimodal. The first large block of trading occurs shortly after the filing of the case ($t_1$). Towards the end of the case, there is another, significantly smaller, period of high trading intensity. Very little trading occurs in the middle of cases. On a volume-weighted basis, 91% of all trades happen in the first half of a bankruptcy case. Given that the complete and comprehensive distribution of claims' holdings, with names and addresses (the new information) is released at $t_1$, the fact that most of the trading takes place immediately following the bankruptcy is consistent with a competitive market for claims in bankruptcy.

20 $\frac{Pr(\text{Traded|Voting})}{Pr(\text{Traded|Non-voting})} = \frac{16\% * (1-5\%)}{(1-16\%) * 5\%} = 3.6$ .

## 2.4. Creditor Concentration and Bankruptcy Outcomes

In what follows, we measure the concentration of ownership as the aggregate share of bankruptcy claims owned by the ten largest creditors in the firm.[21] Throughout the regression analysis we include firm-specific controls that have been found to affect bankruptcy outcomes. Moulton and Thomas (1993) and Campbell (1996) identify the size of the firm and profitability as key variables influencing bankruptcy outcomes. To account for this, we control for the logarithm of asset size, based on the assets reported by firms in their original Chapter 11 petitions. (In general, our results are robust to exclusion of the 10 largest or 10 smallest firms from the analysis.) Profitability is measured using an indicator variable equal to one if the firm had positive EBITDA prior to filing and zero otherwise. As shown in Table 2.1, only limited information is available for pre-bankruptcy EBITDA. To account for this, we control for the level effect for those firms that have EBITDA data available. Motivated by Acharya, Bharath and Srinivasan (2007), each regression also includes industry fixed effects, for which we aggregate firms into (i) mining and construction; (ii) manufacturing; (iii) services; (iv) transportation, communication, and utilities; (v) wholesale and retail trade; and (vi) finance, insurance, and real estate.

Finally, we include a dummy variable equal to one when a firm files for bankruptcy during a recession, as defined by the National Bureau of Economic Research (NBER). Controlling for economic downturns is important because the bankruptcy experience is likely to be different for firms that file during a recession. For instance, as shown in Chapter 1, bankruptcy caseloads are much heavier during recessions, giving judges and attorneys less time to devote to each case. Also, negotiations between creditors likely differ because outside options are worse during these times or because it is more difficult

[21] In an earlier version of the essay, we used the dollar-weighted Herfindahl-Hirschman Index (HHI) to measure ownership concentration across the entire capital structure. Our current measure is more conservative, since it only counts the largest claimholders. However, the two measures are highly correlated, and by either measure we find that trading leads to higher concentration.

to obtain in-bankruptcy financing. It is also possible that firms filing for bankruptcy in a recession are intrinsically different from firms that default in normal times.[22]

In the subsequent tables our sample size decreases from 136 to 119 observations. For 14 firms in our sample the claims administrators that provided data for this study were hired only to perform the voting tabulation at $t_2$, so we did not receive ownership data at the filing of schedules and registers ($t_1$). For an additional three firms we were unable to obtain data on total assets.

#### *2.4.1. Creditor concentration at the onset of bankruptcy*

##### *2.4.1.1. Determinants of creditor concentration at $t_1$*

Our focus is on trading in bankruptcy. But strategic consolidation of ownership often takes place before the bankruptcy filing. So, we start by exploring factors that relate to creditor concentration at the bankruptcy filing, with a specific focus on potentially strategic trading. The goal of this analysis is twofold. As discussed above, claims held by non-financial corporations cannot be easily traded in advance of the bankruptcy filing. So, first, we want to confirm that a large presence of such corporate claims leads to lower pre-bankruptcy ownership concentration. Second, we want to see if there is evidence that pre-bankruptcy trading is related to ownership consolidation. The results are reported in Table 2.4.

The first set of explanatory variables ("Capital structure") includes the share of claims owned by non-financial corporations and by active investors, and three dummy variables equal to one when bank debt, public debt, or either bank or public debt represent more than 5% of the debt structure of the bankrupt firm. Amounts less than 5% of the capital structure are unlikely to have a large effect on the

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[22] We also verify (unreported) that our results—including the effect of trade on ownership and the effect of ownership on the bankruptcy outcomes—are not driven by cases filed in Delaware or Southern New York, cases filed in 2008 and 2009, or cases filed after 2005 amendments to the U.S. bankruptcy law. Regarding this last point, there seems to be a common belief that 2005 changes might have increased the frequency of prearranged bankruptcies; so, when looking at bankruptcy outcomes we will explicitly control for prearranged bankruptcies. Finally, Dahiya. John, Puri and Ramirez (2003) show that firms obtaining DIP financing are more likely to emerge from the Chapter 11 process and in a shorter time. We confirm that controlling for DIP financing does not alter our conclusions.

## TABLE 2.4
### DETERMINANTS OF CREDITOR CONCENTRATION AT BANKRUPTCY

This table looks at the determinants of the creditor concentration at bankruptcy. The dependent variable is *Creditor concentration ($t_1$)* measured as the share of claims held by 10 largest creditors at filing of Schedule of Assets and Liabilities (i.e., at bankruptcy filing). Share of claims owned by corporation and active investors are defined exactly as in Table 2.2. *Bank debt* is a dummy equal to 1if the share of bank debt as fraction of total debt is at least 5% and 0 otherwise. *Public debt* is defined similarly. *Bank debt or public debt* is a dummy equal to 1 if either *Bank debt* or *Public debt* is equal to 1 and 0 otherwise. *Traded loan* is a dummy equal to 1if a firms' loan is quoted prior to bankruptcy filing in Markit secondary market database and 0 otherwise. *Loan traded within 1 year of bankruptcy* is defined similarly but restricts to loan quotes that are within 1 year of the bankruptcy filing. *Bond traded within 1 year of bankruptcy* is a dummy variable equal to 1if firm's bond is quoted within 1 year prior to bankruptcy filing in TRACE bond transactions database and 0 otherwise. *Loan or bond traded within 1 year of bankruptcy* is a dummy equal to 1 if either of the previous two dummies is equal to 1 and 0 otherwise. Assets are measured in millions and were compiled from each firms' Chapter 11 petition. *Positive EBITDA* is a dummy variable indicating if the firm had positive EBITDA prior to filing. Only limited information is available for pre-bankruptcy EBITDA. To account for this, we control for the level effect for those firms that have EBITDA data available. *Economic recession* is a dummy equal to 1 if the firm files for bankruptcy during a recession period, as defined by National Bureau of Economic Research. All models are estimated using linear least squares. Standard errors are clustered by industry and reported in parenthesis. ***, ** and * indicate statistical significance at 1%, 5%, and 10% level, respectively.

| Dependent variable: | Creditor concentration ($t_1$) | | | | |
|---|---|---|---|---|---|
| Capital structure: | | | | | |
| Share of claims owned by corporation | -0.166*** | -0.146*** | -0.174*** | -0.164*** | -0.149** |
| | (0.034) | (0.032) | (0.030) | (0.029) | (0.038) |
| Share of claims owned by active investors | 0.064 | 0.087 | 0.065 | 0.064 | 0.068 |
| | (0.063) | (0.069) | (0.065) | (0.061) | (0.075) |
| Bank debt (dummy) | 0.004 | 0.025 | 0.032 | -- | -- |
| | (0.051) | (0.051) | (0.049) | | |
| Public debt (dummy) | 0.074** | -- | -- | 0.073 | -- |
| | (0.021) | | | (0.049) | |
| Bank or public debt (dummy) | -- | -- | -- | -- | 0.047 |
| | | | | | (0.063) |
| Pre-bankruptcy trading: | | | | | |
| Traded loan | -- | 0.070* | -- | -- | -- |
| | | (0.033) | | | |
| Loan traded within 1 year of bankruptcy | -- | -- | 0.032 | -- | -- |
| | | | (0.020) | | |
| Bond traded within 1 year of bankruptcy | -- | -- | -- | 0.023 | -- |
| | | | | (0.061) | |
| Loan or bond traded within 1 year of bankruptcy | -- | -- | -- | -- | 0.064** |
| | | | | | (0.024) |
| Ln(Assets) | -0.013 | -0.016* | -0.014 | -0.013 | -0.016* |
| | (0.007) | (0.008) | (0.008) | (0.008) | (0.008) |
| EBITDA data available | -0.067 | -0.044 | -0.043 | -0.066 | -0.058 |
| | (0.045) | (0.027) | (0.032) | (0.047) | (0.040) |
| Positive EBITDA | 0.053 | 0.047 | 0.051 | 0.051* | 0.043 |
| | (0.028) | (0.035) | (0.032) | (0.023) | (0.034) |
| Economic recession | 0.011 | 0.001 | 0.009 | 0.011 | 0.006 |
| | (0.020) | (0.017) | (0.017) | (0.021) | (0.018) |
| Observations | 119 | 119 | 119 | 119 | 119 |
| *R*-squared | 0.133 | 0.139 | 0.120 | 0.134 | 0.143 |

overall capital structure at $t_1$, nor are they likely to be of strategic importance to traders interested in taking positions in the capital structure using loans and bonds.

While we cannot observe out-and-out pre-bankruptcy trading, we can have proxies for trading activity in loans and bonds. Four such proxies are grouped under "Pre-bankruptcy trading". Following Drucker and Puri (2009), we use the existence of pre-filing secondary market price quotes for loans in our sample firms as a proxy for whether a firm's loans are traded prior to filing. The price quotes are collected via dealer surveys conducted by Markit. We look at whether a given firm had loans traded within a year of bankruptcy. We also examine a more open-ended measure of loan trading that equals one when a quote for the loan appears within five years of bankruptcy filing. Following Goldstein, Hotchkiss, and Sirri (2007) and Bessembinder and Maxwell (2008), using the FINRA Trade Reporting and Compliance Engine (TRACE) dataset, we track whether there were trades in the bonds and notes of our sample firms in the one year leading to the bankruptcy. We define separate dummy variables that equal one when there is evidence of loan trading, bond trading, and loan or bond trading within one year prior to the bankruptcy filing.

Several notable patterns emerge from the regressions in Table 2.4. Most distinctly, creditor concentration at $t_1$ is decreasing in the share of corporate claims owned by corporations, implying that firms in which trade claims represent a large part of the capital structure enter Chapter 11 with a less concentrated ownership than firms with fewer trade claims. The magnitude of the estimates are economically large: a one standard deviation increase in the share of claims owned by corporations (22%) reduces the proportion of holdings by the top ten creditors by 3 to 4 percentage points. Meanwhile, the share of claims held by active investors appears to have no discernible impact on $t_1$ concentration, the estimates are statistically insignificant in each case.

The estimates associated with the pre-bankruptcy trading variables show that debt ownership structures are more concentrated at $t_1$ when there was trading in a firm's debt prior to the filing, consistent with the idea that pre-filing trading increases creditor concentration. The top ten largest creditors own 7 percentage points more of the debt in firms that experienced a loan trade prior to filing, and 6.4 percentage points more of the debt in firms that experience a loan or bond trade within one year of filing. Importantly, these results are conditional on the presence of a bank loan or public bond, so they are not just picking up the fact that firms with these debt instruments have more concentrated capital structures, but instead indicate that trading prior to bankruptcy is indicative of a more concentrated ownership structure. While the pre-bankruptcy trading variables are rough indicators of actual trading in a firm's instruments, they suggest that investors acquiring claims in a distressed firm prior to filing concentrate the ownership structure of firms prior to filing for Chapter 11.

##### *2.4.1.2. Creditor concentration at $t_1$ and bankruptcy outcomes*

The takeaway from Table 2.4 is that creditor concentration at $t_1$ is lower in debt structures that contain a high share of corporate claims, and higher in structures in which loan and bond trading is observed prior to filing. We now turn to examining the extent to which creditor concentration at $t_1$ explains outcomes of the Chapter 11 restructuring.

Table 2.5 reports results in which characteristics of the Chapter 11 restructuring are regressed on creditor concentration at $t_1$ and other control variables. We focus on four dependent variables in the regressions: (i) an indicator variable equal to one if the bankruptcy filing was prearranged or "prepackaged", so that much of the restructuring negotiations occur out of court prior to filing; (ii) the number of months the firm remains in bankruptcy; (iii) a set of dummy variables identifying the bankruptcy outcome according to whether a firm exits Chapter 11 through a traditional reorganization, a going-concern 363 sale, or through a piecemeal liquidation; and (iv) the overall recovery rate.

The results in Table 2.5 show a distinct pattern. Firms are significantly more likely to restructure through a pre-arranged filing, spend a shorter time in bankruptcy, and emerge via a reorganization of the existing entity when debt ownership is more concentrated at $t_1$. The estimates in the first column of Table 2.5, Panel A imply that for every one standard deviation (17%) increase in creditor concentration, the likelihood that the restructuring is completed through a pre-arranged agreement rises by 6.3 percentage

## TABLE 2.5

### CREDITOR CONCENTRATION AT BANKRUPTCY FILING AND BANKRUPTCY OUTCOME

This table examines the relation between the concentration of creditors in a bankrupt firm and variables measuring the outcome of the bankruptcy. The central explanatory variable is *Creditor concentration ($t_1$)* measured as the share of claims held by 10 largest creditors at filing of Schedule of Assets and Liabilities (i.e., at bankruptcy filing). Panel B extends results in Panel A by adding proxies of ownership concentration used in the previous literature. *Bank debt/Total debt* and *Public debt/Total debt* are measured at the end of the fiscal year prior to filing. *Bank debt or public debt* is a dummy equal to 1 if the firm has either bank or public debt and 0 otherwise. Note that, given the objective of the tables, these additional controls are defined differently from the controls used in Table 2.4. Assets are measured in millions and were compiled from each firms' Chapter 11 petition. *Positive EBITDA* is a dummy variable indicating if the firm had positive EBITDA prior to filing. Only limited information is available for pre-bankruptcy EBITDA. To account for this, we control for the level effect for those firms that have EBITDA data available. *Economic recession* is a dummy equal to 1 if the firm files for bankruptcy during a recession period, as defined by National Bureau of Economic Research. All models are estimated using linear least squares. Standard errors are clustered by industry and reported in parenthesis. ***, ** and * indicate statistical significance at 1%, 5%, and 10% level, respectively.

*Panel A: Creditor concentration at filing of Schedule of Assets and Liabilities ($t_1$), all creditors*

| Dependent variable: | Prearranged bankruptcy | Time in bankruptcy (months) | Outcome: | | | Recovery rate |
|---|---|---|---|---|---|---|
| | | | Reorganization | Sale | Liquidation | |
| Creditor concentration ($t_1$) | 0.371*** | -6.671** | 0.389** | 0.073 | -0.465 | -1.096 |
| | (0.089) | (2.240) | (0.135) | (0.297) | (0.353) | (0.616) |
| Prearranged bankruptcy | -- | -8.171*** | 0.153* | 0.146 | -0.279** | 0.052 |
| | | (1.092) | (0.062) | (0.088) | (0.072) | (0.052) |
| Ln(Assets) | 0.001 | 0.955*** | 0.069** | -0.031 | -0.033 | -0.040 |
| | (0.019) | (0.228) | (0.018) | (0.019) | (0.026) | (0.026) |
| EBITDA data available | -0.017 | -2.375 | -0.190* | 0.082 | 0.106 | -0.106* |
| | (0.091) | (1.789) | (0.093) | (0.096) | (0.094) | (0.045) |
| Positive EBITDA | 0.049 | 0.987 | 0.314** | -0.138 | -0.203 | 0.322*** |
| | (0.097) | (1.342) | (0.102) | (0.146) | (0.178) | (0.060) |
| Economic recession | 0.109 | -4.935* | 0.198* | -0.243*** | 0.027 | -0.073 |
| | (0.147) | (2.119) | (0.094) | (0.054) | (0.101) | (0.045) |
| Industry Fixed Effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 119 | 115 | 119 | 119 | 119 | 108 |
| *R*-squared | 0.10 | 0.35 | 0.22 | 0.12 | 0.14 | 0.07 |

**Table 2.5** – *continued*

*Panel B: "Horse race" comparison of ownership concentration measures*

| Dependent variable: | Prearranged bankruptcy | Time in bankruptcy (months) | Outcome: Reorganization | Outcome: Sale | Outcome: Liquidation | Recovery rate |
|---|---|---|---|---|---|---|
| Creditor concentration ($t_1$) | 0.355*** | -7.339** | 0.390** | 0.062 | -0.480 | -1.017 |
| | (0.087) | (2.506) | (0.125) | (0.308) | (0.407) | (0.545) |
| Bank debt/Total debt | 0.104 | 1.643 | -0.060 | -0.020 | 0.209 | -0.136** |
| | (0.108) | (2.313) | (0.268) | (0.256) | (0.176) | (0.037) |
| Public debt/Total debt | 0.138 | 4.919 | -0.036 | 0.043 | 0.137 | -0.049 |
| | (0.171) | (3.760) | (0.130) | (0.097) | (0.139) | (0.041) |
| Bank or public debt (dummy) | -0.119 | -2.883 | 0.054 | -0.020 | -0.140 | -0.075 |
| | (0.077) | (2.742) | (0.107) | (0.134) | (0.083) | (0.099) |
| Prearranged bankruptcy | -- | -8.278*** | 0.155* | 0.146 | -0.287** | 0.047 |
| | | (1.066) | (0.062) | (0.097) | (0.074) | (0.043) |
| Ln(Assets) | 0.005 | 1.030*** | 0.067*** | -0.030 | -0.030 | -0.033 |
| | (0.021) | (0.240) | (0.016) | (0.016) | (0.026) | (0.027) |
| EBITDA data available | -0.026 | -3.061 | -0.193** | 0.078 | 0.092 | -0.047* |
| | (0.134) | (2.439) | (0.067) | (0.128) | (0.115) | (0.022) |
| Positive EBITDA | 0.054 | 1.192 | 0.315** | -0.133 | -0.204 | 0.321*** |
| | (0.091) | (1.680) | (0.092) | (0.161) | (0.182) | (0.052) |
| Economic recession | 0.110 | -4.873* | 0.198 | -0.239** | 0.022 | -0.055 |
| | (0.165) | (2.311) | (0.098) | (0.060) | (0.107) | (0.049) |
| Industry Fixed Effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 119 | 115 | 119 | 119 | 119 | 108 |
| *R*-squared | 0.055 | 0.368 | 0.226 | 0.121 | 0.173 | 0.188 |

points. While pre-arranged deals are likely also to move much faster through Chapter 11, the second column of Table 2.5, Panel A shows that when the incidence of a pre-arranged filings is held constant, the time spent restructuring in Chapter 11 declines by 1.13 months for every one standard deviation increase in creditor concentration. In other words, a more concentrated debt structure is associated with a shorter time in a bankruptcy even after controlling for the effect of prearranged filings. Meanwhile, the estimates in the middle columns of Table 2.5, Panel A imply that likelihood of emerging from bankruptcy via a reorganization increases 6.6 percentage points for every one standard deviation increase in creditor concentration. The large negative coefficient on creditor concentration in the liquidation regression (-0.465) also suggests that more concentrated debt structures are less likely to end in a piecemeal liquidation, although the implied *t*-statistic of -1.31 (-0.465/0.353) is not statistically significant at conventional levels.

Taken together, the results in Table 2.5, Panel A suggest that Chapter 11 restructurings move more quickly when the debt ownership is concentrated at $t_1$, in the sense that they are more likely to complete their bargaining out of court prior to filing, and even when filing through a traditional "free fall" bankruptcy, restructure more quickly in bankruptcy. Moreover, more concentrated structures are associated with a higher likelihood of successfully emerging as a reorganized firm, and possibly, a lower likelihood of liquidating piecemeal. If we couple the results from Table 2.5 with the inferences from Table 2.4, our findings thus far suggest that debt ownership structures with lower levels of corporate claims and higher levels of pre-filing trading are associated with quicker restructurings.

One of the contributions of our essay is improvement over ownership concentration measures used in the previous literature. Correlations between our measures of creditor concentration and proxies used in earlier papers are quite low, highlighting the improvement in measurement provided by our study. In particular, the correlation between the share of claims owned by the ten largest claimholders at $t_1$ and bank debt as a fraction of total debt—used by Gilson (1990), Gilson, John, and Lang (1990) among other studies—is 0.18 and statistically insignificant at conventional levels. The correlation between our concentration variable and public debt as a fraction of total debt—used by Brown, James, and Mooradian (1993), Asquith, Gertner and Scharfstein (1994), and James (1995, 1996)—is 0.21 and only marginally statistically significant. Consistent with these low correlations, the results in Panel B (where we include all of these proxies together with our creditor concentration measure) indicate that our finding are unaffected by this "horse race" analysis. Moreover, none of the raw proxies of ownership concentration are important in explaining the bankruptcy outcomes.

#### *2.4.2. Creditor concentration at the end of bankruptcy*

##### *2.4.2.1. Claims trading and creditor concentration*

The evidence presented in Table 2.3 establishes the existence of an active market for claims trading during bankruptcy. This is an important and novel fact because the concentration of ownership, and heterogeneity in this concentration across firms, is believed to influence bankruptcy costs (Gertner and Scharfstein, 1991; Bolton and Scharfstein, 1996). If we take as a given that debt ownership concentration impacts bankruptcy restructurings, then trading that leads to significant consolidation in ownership could have an effect on bankruptcy outcomes. In this sub-section, we assess the effect of trading on ownership concentration.

The evidence in Table 2.4 already suggests that consolidation of ownership takes place before bankruptcy through trading in loans and bonds, so the fact that there are changes in ownership during the bankruptcy process might not be that surprising. But there is an additional insight from observing bilateral claims trading directly during the bankruptcy process. As we discuss in Section 2.3.2, bilateral claims often lie in the strategically important middle of the capital structure, where claimholders likely are entitled to vote on a plan, and often end up in the fulcrum voting class. Given that there is almost no market for bilateral claims before the bankruptcy filing, these claims are transacted only in bankruptcy and we observe virtually all of these trades. And while many traders will take positions in the capital structure prior to filing to attempt to influence the restructuring (both before and during the bankruptcy filing), there is a lot of room during bankruptcy to take strategic positions, particularly in the set of corporate claims that are difficult to trade before the filing. Moreover, the Chapter 11 process reveals a lot of new information about the bankrupt firm that could provide incentives to trade. In short, the possibility of trading in bilateral claims, and trading in bankruptcy more broadly, has the potential to influence the control of ownership and, hence, bankruptcy outcomes. The fact that claims are actively transacted in bankruptcy is a relevant insight for understanding the efficiency of the bankruptcy process.

Tables 2.2 and 2.3 suggest a positive association between claims trading during the case and ownership concentration at the end of the case. Table 2.6 examines this relation directly by regression debt ownership concentration at $t_2$ on *Claims trading intensity*, which is a discrete variable that takes the values of 0, 1, 2, or 3 based on the amount of bilateral claims trading observed in a sample firm during the bankruptcy. The variable equals 0 when no trading is observed. The remaining firms are coded with a 1, 2, or 3 to correspond to the tercile of the share of traded claims that occur in the firm.

The first two columns of Panel A of Table 2.6 report regressions using the level of ownership concentration at $t_2$, measured as the holdings of the 10 largest investors, while the last two columns report similar regressions but with a measure of the change in ownership concentration between $t_1$ and $t_2$. When the dependent variable is the $t_2$ level of concentration, we also control for ownership concentration at $t_1$ since trading in bankruptcy can only affect changes in ownership concentration after $t_1$. For the regressions deploying the change in concentration as the dependent variable, we implicitly assume that the distribution of ownership across the capital structure at $t_1$ is a good proxy for the distribution of ownership among voting classes at $t_2$.[23]

The regression results indicate a strong positive relation between intensity of bilateral claims trading and both the level of creditor concentration at the end of the case and the change in creditor concentration over the course of the case. The ordinary least squares (OLS) estimates imply that moving from having no recorded bilateral claims to being in the third tercile of trading (i.e. an increase of 3 in *claims trading intensity*) results in a 0.43 standard deviation increase in the overall level of creditor concentration, and a 0.80 standard deviation increase in the change in concentration between the register and tabulation. As mentioned earlier, the trading of bilateral claims probably reflects a lower bound on general trading in bankruptcy. Based on these results, we conclude that trading in bankruptcy leads to

[23] Using the 36 cases from BMC group, we can construct a direct measure of the change in ownership concentration among claims at $t_1$ that are eventually eligible to vote. While the sample size is small, estimates produced by limiting the regressions to these 36 exactly-measured cases are similar to the results using the larger sample. In this sub-sample, we also find that the correlation between the unconditional share of claims owned by the 10 largest claimholders and just voting claims is 0.68, significant at the 1% level.

significant consolidation of ownership. Assuming that $t_1$ overall concentration is a good proxy for $t_1$ concentration of voting classes (fact that we verify in the BMC sample), the causal relation between trading and ownership concentration during bankruptcy is unambiguous because trading is the only way of changing the ownership during the bankruptcy process.

## TABLE 2.6

### CLAIMS TRADING AND CREDITOR CONCENTRATION

This table explores the relation between trading of claims in bankruptcy and changes in the level of creditor concentration during a Chapter 11 case. Panel A presents estimates of the impact of claims trading on the concentration of creditors. The explanatory variable of interest *Claims trading intensity* is equal 0 if there is no trading in bilateral claims (56 out of 119 cases). For the remaining firms, the share of traded bilateral claims is sorted in terciles; *Claims trading intensity* is equal to 1 for firms in the first tercile (20 firms), 2 for firms in the second tercile (24 firms), and 3 for the firms the third tercile (19 firms). Panel B reports results of the first-stage regressions. *Share of mid-size claims owned by corporation* is defined as total amount of claims between $100,000 and $300,000 that is owned by corporations scaled by the firm's total amount of all claims at bankruptcy. *Share of claims owned by corporations* is defined as the total amount of claims owned by corporations scaled by the firm's total amount of all claims at bankruptcy. Assets are measured in millions and were compiled from each firms' Chapter 11 petition. *Positive EBITDA* is a dummy variable indicating if the firm had positive EBITDA prior to filing. Only limited information is available for pre-bankruptcy EBITDA. To account for this, we control for the level effect for those firms that have EBITDA data available. *Economic recession* is a dummy equal to 1 if the firm files for bankruptcy during a recession period, as defined by National Bureau of Economic Research. All models are estimated using linear least squares. Standard errors are clustered by industry and reported in parenthesis. ***, ** and * indicate statistical significance at 1%, 5%, and 10% level, respectively.

*Panel A: Claims trading and creditor concentration*

| Dependent variable: | Creditor concentration at voting tabulation ($t_2$) | | Change in creditor concentration ($t_2 - t_1$) | |
|---|---|---|---|---|
| | OLS | 2SLS | OLS | 2SLS |
| Claims trading intensity | 0.025** | 0.078** | 0.044*** | 0.116*** |
| | (0.011) | (0.036) | (0.014) | (0.027) |
| Creditor concentration ($t_1$) | 0.626*** | 0.750*** | -- | -- |
| | (0.113) | (0.155) | | |
| Ln(Assets) | -0.030*** | -0.036*** | -0.031*** | -0.040*** |
| | (0.006) | (0.007) | (0.006) | (0.007) |
| EBITDA data available | 0.059* | 0.068* | 0.074** | 0.081* |
| | (0.030) | (0.039) | (0.036) | (0.048) |
| Positive EBITDA | -0.112*** | -0.124*** | -0.138*** | -0.142*** |
| | (0.038) | (0.043) | (0.043) | (0.050) |
| Economic recession | -0.064** | -0.034 | -0.064** | -0.017 |
| | (0.026) | (0.036) | (0.028) | (0.038) |
| Industry fixed effects | Yes | Yes | Yes | Yes |
| Observations | 119 | 119 | 119 | 119 |
| $R$-squared | 0.51 | -- | 0.35 | -- |

**TABLE 2.6** – *continued*

*Panel B: First stage (for 2SLS)*

| Dependent variable: | Claims trading intensity | | |
|---|---|---|---|
| Instruments: | | | |
| Share of mid-size claims owned by corporation | 11.027*** | 12.023*** | -- |
| | (3.091) | (3.327) | |
| Share of claims owned by corporation | 0.939** | -- | 1.082** |
| | (0.471) | | (0.484) |
| Creditor concentration ($t_1$) | -1.373* | -1.639** | -1.986*** |
| | (0.735) | (0.713) | (0.720) |
| Ln(Assets) | 0.184*** | 0.158*** | 0.152*** |
| | (0.047) | (0.052) | (0.044) |
| EBITDA data available | -0.249 | -0.219 | -0.218 |
| | (0.341) | -0.343 | (0.338) |
| Positive EBITDA | 0.355 | 0.314 | 0.267 |
| | (0.350) | (0.354) | (0.355) |
| Economic recession | -0.438** | -0.503** | -0.485** |
| | (0.190) | (0.195) | (0.190) |
| Industry fixed effects | Yes | Yes | Yes |
| *F*-stat | 10.25 | 13.06 | 5.01 |
| *p*-value | 0.00 | 0.00 | 0.03 |
| Observations | 119 | 119 | 119 |
| *R*-squared | 0.34 | 0.32 | 0.30 |

#### *2.4.2.2. Creditor concentration at $t_2$ and bankruptcy outcomes*

As a final point of this chapter we want to connect changes in ownership concentration in bankruptcy to restructuring outcomes. Observed claims transfers could be related to debt ownership concentration through mechanisms that could be related to the bankruptcy. For instance, trading activity could be higher in the middle of the capital structure when firms have lower valuations (because the potential upside on a fixed debt instrument is higher), and these firms could be more difficult to restructure. In this case, the relation between trade and outcomes, and changes in ownership and outcomes would not be causal. To address this issue, we use an instrumental variables approach. Because trading is central to the changes in the ownership concentration, we look for a variable that influences trading activity but is likely to be independent of the fact that the firm is in bankruptcy. Specifically, we use two variables: *Share of claims owned by corporations* defined as the total amount of claims owned by corporations scaled by the firm's total amount of all claims at bankruptcy, and *Share of mid-size claims owned by corporation,* defined as the total amount of claims whose value is between $100,000 and $300,000 that are owned by corporations, scaled by the firm's total amount of all claims at bankruptcy. The first variable reflects the structure of corporate (non-financial) credit; the cut-offs correspond to the bounds of the second, medium tercile of the cross-sectional distribution claims size.[24] We explicitly control for firm size in the regressions, but we obtain similar results if we construct the cutoffs after scaling claims by firm size, instead of using absolute cutoffs.

The central reason why we choose instruments based on the amount and characteristics of the corporate non-financial claims is that corporations that are trade suppliers—most of the corporate non-financial claims—are among the least likely to hold on to their claims through bankruptcy. The level of a firm's non-corporate claims are likely to be set well in advance of the firm's financial distress, and are determined by factors related to the firm's operating and sales strategies. As we have shown, corporations represent a significant part of the filing firms' ownership structure (present in 97% of bankruptcy cases), and they tend to be concentrated in classes of "general unsecured" voting claims. We have also shown that corporations are large net sellers of claims. Because of this, firms with more trade credit are expected to have more claims available for sale; in other words, the basic idea behind using trade credit as an instrument for ownership concentration is that a bigger supply of claims for sale leads to more opportunities to consolidate such claims. Our second instrument focuses on the structure of these claims. Specifically, small claims are costly to transact, whereas large claims often carry a strategic interest for the supplier in that a large supplier might be interested in retaining its trade claim to preserve a good relationship with the bankrupt firm. Thus, mid-size claims are most likely to be available for sale. In the

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[24] $Share\ of\ mid\ size\ claims_i = \frac{\sum_{j|M} C_{ij}}{\sum_j C_{ij}}, M = \left\{Cj: Corporate\ claims\ \cap\ T_1 < C_{ij} < T_2\right\}$ . $C_{ij}$ is the claim $j$ for bankruptcy case *i*, *T1* and *T2* indicate cross-sectional terciles cut-offs for corporate claims.

appendix, we use to details of our claims data to show that, indeed, medium size claims are more likely to be sold than large or small clams.

The composition of trade credit is unlikely to change dramatically in anticipation of bankruptcy through claims sales to third parties. Prior to bankruptcy, investors looking to purchase distressed trade credit lack a market in which they can identify trade creditors who are looking to reduce their exposure to distressed firms. Once the bankruptcy occurs and the schedules and claims register are created, trading is much easier because the identities of trade creditors become available. Consistent with this, we find in unreported results that the vast majority of trading in bankruptcy happens in the first few months after the bankruptcy filing, just after the list of creditors becomes publically available. So, because most trading of trade credit claims occurs in bankruptcy, even if the bankruptcy is anticipated, we can accurately assess change in ownership resulting from transfers of trade claims during the bankruptcy process. It is possible that trade partners could understand better the nature of the assets (Petersen and Rajan, 1997), —and potential outcome of the bankruptcy process—and change their trade credit policy in anticipation of financial distress, but the possibility of suppliers "investing" in soon-to-be bankrupt firms because they understand a firm's future is inconsistent with the relatively small economic value of such investments for any given supplier, and the fact that most of the trade claims are sold in bankruptcy at presumably a large discount. In addition, the size of each individual trade claim is determined mostly by the economic size of the transaction between the parties, not the potential outcome of the bankruptcy case. Because of this, the *mid-sized claims* instrument is also likely exogenous to eventual bankruptcy outcomes.

In light of these arguments, our instruments are likely to satisfy the exclusion restriction that the composition of corporate credit does not change in anticipation of bankruptcy outcomes. In addition, the instruments should not be correlated with third factors that are likely to affect the bankruptcy outcomes, *conditional* on the observables. As mentioned previously, we control for the set of firm characteristics that previous researchers have found to influence bankruptcy outcomes. Consistent with Acharya, Bharath and Srinivasan (2007), our analysis includes industry fixed effects. Moulton & Thomas (1993) and Campbell (1996) identify the size of the firm and profitability as key variables; we control for both in all regressions.[25] Thus, while our instruments are not fundamentally exogenous (they are not a result of a natural experiment), they satisfy the conditional independence assumption if they are unrelated to bankruptcy outcomes conditional on firm size, profitability, and industry.

Panel B in Table 2.6 reports results of the first-stage regressions. The table shows a strong positive relation between share of mid-size claims owned by corporations and trade intensity. The *F*-statistic for the exclusion of the instrumental variables is 10.25 with *p*-values close to zero. Each of the variables is also individually significant. The correlation between *mid-size claims* and *share of claims owned by corporations* is 0.31, so there is a fair amount of unexplained variation that each variable picks up separately. In the first-stage regressions, adjusted *R*-squared without the instruments included (unreported) is 0.27. The inclusion of the instruments increases the *R*-squared to 0.32 for mid-size claims alone, 0.30 for share of total claims alone, and 0.34 with when both variables are present.

The two stage least squares (2SLS) estimates of the impact of claims trading on the creditors concentration of creditors are reported in columns two and four of Panel A, Table 2.6. The 2SLS results are largely consistent with the OLS estimates. This result is also robust to estimation using limited information maximum likelihood (LIML), which is more robust to weak instruments than two-stage least squares (2SLS).

As mentioned earlier, the instrumental variable approach is relevant for our understanding of the impact of ownership concentration on the bankruptcy restructuring. In Table 2.7, we present the results of regressions relating bankruptcy restructuring characteristics to ownership concentration measured at the vote tabulation ($t_2$). The table includes results using both OLS and 2SLS. As in Table 2.5, the results are a cross-sectional comparison at the firm level. Throughout, we control for the initial ($t_1$) claims

[25] Dahiya. John, Puri and Ramirez (2003) show that firms obtaining DIP financing are more likely to emerge from the Chapter 11 process and in a shorter time. In unreported regressions we control for DIP financing but do not find that it alters our results in any substantial way.

concentration in order to focus on the effect that claims trading has on concentration during the bankruptcy process.

## TABLE 2.7
### CREDITOR CONCENTRATION AT PLAN VOTING AND BANKRUPTCY OUTCOME

This table examines the relation between the concentration of creditors at voting on the Plan of Reorganization ($t_2$) and the bankruptcy outcomes. The central explanatory variable is *Creditor concentration* ($t_2$) measured as share of claims held by 10 largest creditors at voting on the Plan of Reorganization. We control for the creditor concentration at filing of the Schedule of Assets and Liabilities, *Creditor concentration* ($t_1$). Panel A presents OLS results and Panel B presents 2SLS results. In Panel B creditor concentration is instrumented using variables discussed in Table 2.6. Assets are measured in millions and were compiled from each firms' Chapter 11 petition. *Positive EBITDA* is a dummy variable indicating if the firm had positive EBITDA prior to filing. Only limited information is available for pre-bankruptcy EBITDA. To account for this, we control for the level effect for those firms that have EBITDA data available. *Economic recession* is a dummy equal to 1 if the firm files for bankruptcy during a recession period, as defined by National Bureau of Economic Research. All models are estimated using linear least squares. Standard errors are clustered by industry and reported in parenthesis. ***, ** and * indicate statistical significance at 1%, 5%, and 10% level, respectively.

*Panel A: Bankruptcy outcomes (OLS)*

| Dependent variable: | Time in bankruptcy (months) | Outcome: Reorganization | Outcome: Sale | Outcome: Liquidation | Recovery rate |
|---|---|---|---|---|---|
| Creditor concentration ($t_2$) | -1.937 | -0.515 | 0.059 | 0.345 | -0.504* |
| | (5.118) | (0.314) | (0.269) | (0.430) | (0.239) |
| Creditor concentration ($t_1$) | -5.719 | 0.692** | 0.027 | -0.657* | -0.768 |
| | (4.227) | (0.200) | (0.257) | (0.304) | (0.708) |
| Prearranged bankruptcy | -8.258*** | 0.125 | 0.150 | -0.261*** | 0.016 |
| | (1.054) | (0.085) | (0.097) | (0.054) | (0.060) |
| Ln(Assets) | 0.894*** | 0.056* | -0.029 | -0.024 | -0.055* |
| | (0.128) | (0.022) | (0.023) | (0.029) | (0.022) |
| EBITDA data available | -2.282 | -0.161 | 0.079 | 0.087 | -0.079 |
| | (1.999) | (0.100) | (0.102) | (0.093) | (0.046) |
| Positive EBITDA | 0.793 | 0.260** | -0.131 | -0.168 | 0.267** |
| | (1.558) | (0.080) | (0.162) | (0.155) | (0.080) |
| Economic recession | -5.081** | 0.160 | -0.239*** | 0.052 | -0.111 |
| | (1.828) | (0.103) | (0.054) | (0.118) | (0.065) |
| Industry Fixed Effects | Yes | Yes | Yes | Yes | Yes |
| Observations | 115 | 119 | 119 | 119 | 108 |
| *R*-squared | 0.40 | 0.33 | 0.17 | 0.30 | 0.20 |

**TABLE 2.7** – *continued*

*Panel B: Bankruptcy outcomes (2SLS)*

| Dependent variable: | Time in bankruptcy (months) | Outcome: Reorganization | Sale | Liquidation | Recovery rate |
|---|---|---|---|---|---|
| Creditor concentration ($t_2$) | 48.896 | -4.887 | 0.604 | 3.192* | -3.655*** |
| | (60.035) | (3.112) | (2.406) | (1.704) | (1.089) |
| Creditor concentration ($t_1$) | -34.042 | 3.259** | -0.282 | -2.339** | 1.140*** |
| | (33.817) | (1.342) | (1.444) | (1.000) | (0.381) |
| Prearranged bankruptcy | -5.712* | -0.114 | 0.179 | -0.105 | -0.200* |
| | (3.333) | (0.270) | (0.153) | (0.129) | (0.113) |
| Ln(Assets) | 2.351 | -0.062 | -0.015 | 0.052 | -0.144*** |
| | (1.911) | (0.080) | (0.064) | (0.049) | (0.049) |
| EBITDA data available | -5.067 | 0.070 | 0.050 | -0.064 | 0.100 |
| | (3.910) | (0.123) | (0.149) | (0.079) | (0.087) |
| Positive EBITDA | 6.083 | -0.197 | -0.075 | 0.130 | -0.062 |
| | (7.552) | (0.345) | (0.328) | (0.130) | (0.119) |
| Economic recession | -1.050 | -0.154 | -0.200 | 0.257 | -0.346*** |
| | (3.404) | (0.269) | (0.147) | (0.174) | (0.045) |
| Industry Fixed Effects | Yes | Yes | Yes | Yes | Yes |
| Observations | 115 | 119 | 119 | 119 | 108 |

The most notable takeaway of this analysis is that ownership concentration at voting (regardless of the methodology) has largely a different effect on the bankruptcy outcome than ownership concentration at the time of filing for Chapter 11. The concentration of claimants at $t_2$ especially seems to impact the likelihood of liquidation and overall recovery rates. Based on OLS estimates, a one standard deviation increase in creditor concentration at exit increases the probability of being liquidated by 6.0 percentage points, which represents a 18.3% increase from the unconditional likelihood of liquidation. The same increase in $t_2$ concentration is also associated with an 8.8 percentage point reduction in recovery rates, a 16% reduction from the unconditional mean of 54.8%. The magnitude and statistical significance of these results are even higher based on 2SLS estimates. The explanatory power of the regressions (as measured by $R$-squared) in Table 2.7 increase substantially with the inclusion of $t_2$ concentration, compared to the regressions in Table 2.5, suggesting that changes to concentration during bankruptcy are statistically important at the margin.

So why does trading-related concentration impact bankruptcy outcomes by increasing the likelihood of liquidation and lowering recovery rates? These effects seem counterintuitive in light of the Table 2.5 results and that higher levels of concentration should lower ex-post costs of coordination, which should in turn lead to easier workouts and, possibly, higher recovery rates. In answering this question, we should keep two things in mind. First, claims trading in bankruptcy both consolidates claims ownership and allows new investors to enter the capital structure of the debtor. The findings in Table 2.7 describe the *marginal* impact of $t_2$ concentration, holding the impact of $t_1$ concentration constant. The results suggest that investors who "double-down" on their existing stake or acquire claims for the first time in bankruptcy might be pursuing a strategy that is contrarian to the investors that hold their pre-filing positions constant. Second, as the case itself evolves, investors' strategy for how they want to affect outcomes could change. For instance, as a case proceeds forward in bankruptcy, some claimants may acquire positions to push for a liquidation when the value of a reorganization appears to diminish. In other cases, investors may still view a reorganization as being the best alternative, but work to reorganize under a lower valuation, so as to exclude from participation creditors that are junior in the capital structure. In other words, investors who buy-in during the bankruptcy process might very well have a different skill set and, hence, different objective than investors who buy-in prior to bankruptcy.

It is perhaps most difficult to explain the finding that higher $t_2$ concentration leads to *lower* recovery rates. We consider several potential explanations for this finding. First, we look at whether claims traders concentrate their holdings in firms that are more severely distressed with low expected recoveries. One rationale for sophisticated investors to focus on such companies would be that deeply-discounted debt claims have more upside potential, or perhaps that less sophisticated investors are more willing to sell their claims in cases where bankruptcy negotiations are not going well. If this were the case, then the low recovery rates we observe could merely reflect lower ex-ante valuations, and the recovery rates in firms with high levels of concentration could actually be large relative to their pre-filing expected values. However, the results using the instrumented claims trading amount should not be susceptible to this form of endogeneity. Moreover, when we control for pre-filing estimated recoveries using observable bond prices of bankrupt firms, our result persists.

Second, we examine whether the low recovery rates can be explained by the high concentration of holdings in claims in the fulcrum class, the class of claims that receive the bulk of new equity in restructured firms. Investors in the fulcrum class may have incentives to accept a recovery rate that undervalues their position if in return they obtain larger amounts of new equity in the restructured firm. More broadly, Gilson, Hotchkiss, and Ruback (2000) show that senior creditors have a bias towards lower valuations in restructurings, because the lower valuation "squeezes out" more junior claimants, rendering a larger claim for senior creditors in the restructured firm. In particular, investors in the fulcrum class may have incentives to accept a lower *estimated* recovery rate if in return they obtain larger amounts of new equity in the restructured firm. (Note that the *actual* value of claims is fixed, so understated *estimated* recovery rates would lead to larger allocations toward more senior classes.) However, adding the concentration within the fulcrum class of securities to our regressions does not ameliorate the negative relation between claims concentration and overall recovery rates.

To examine more closely the extent to which concentration influences strategic plays on the valuation of the firm, and therefore expected recovery rates, in Table 2.8 we explore recovery rates disaggregated at the voting-class level. Put differently, we measure the relation between recovery rates received by an individual voting creditor class and the concentration of ownership within the class. All the regressions are value-weighted by class so that small classes do not have a large bearing on the results. We use two alternative ways of computing weights. First we weight each class by the total value of claims in the class divided by the overall value of voting claims. However, using only voting claims as a denominator could miss claims that do not vote on the plan, but nonetheless could be large and have influence on the outcomes of negotiations. Thus, we also report the results using each class total value scaled by total assets (a proxy for the total firm value). Because recovery rates generally follow absolute priority, it is important to control for the relative seniority of each voting class. We do so by including a dummy for secured claimants, as well as administrative and priority classes that are senior to unsecured creditors. We also include a dummy for the fulcrum class, as this class typically has special importance in negotiations.[26] We use the disclosure statement filed with the bankruptcy court to collect information on the expected recovery rate, relative seniority, and type of distribution received (cash, new debt, or new equity) for each class.

**TABLE 2.8**

**CREDITOR CONCENTRATION AND RECOVERY RATES AT THE VOTING-CLASS LEVEL**

The focus of this table is to look at the class level recovery rates. Each observation now corresponds to a voting class; each bankruptcy has more than one class of claimants. *Class-level concentration* is measured as a dollar-weighted Herfindahl-Hirschman Index with a maximum of one, for each voting class. Note that this concentration measure differs from the share of claims owned by the 10 largest creditors (the concentration measure used in Tables 2.5 – 2.7), since there are many voting classes that have less than 10 total creditors. In addition to the reported variables, each regression includes benchmark control variables defined in Table 2.6. For compactness of reporting, we omit other control variables. All models are estimated using linear least squares. Standard errors are clustered by bankruptcy and reported in parenthesis. ***, ** and * indicate statistical significance at 1%, 5%, and 10% level, respectively.

| | Weight: Class amount / Total firm assets | | Weight: Class amount / Total voting claims | |
|---|---|---|---|---|
| Class-level concentration | 0.355*** | 0.416*** | 0.186 | 0.268* |
| | (0.128) | (0.136) | (0.127) | (0.139) |
| Administrative/Priority class | 0.509** | 0.217 | 0.568*** | 0.363 |
| | (0.194) | (0.302) | (0.177) | (0.265) |
| Secured class | 0.506*** | 0.496*** | 0.492*** | 0.449*** |
| | (0.085) | (0.081) | (0.078) | (0.085) |
| Fulcrum class | -- | 0.821*** | -- | 0.689*** |
| | | (0.125) | | (0.133) |
| Fulcrum class*Class concentration | -- | -1.115*** | -- | -1.033*** |
| | | (0.294) | | (0.285) |
| Benchmark controls | Yes | Yes | Yes | Yes |
| Observations | 404 | 404 | 404 | 404 |
| *R*-squared | 0.83 | 0.86 | 0.69 | 0.76 |

Results in Table 2.8 indicate that higher concentration within a voting class has a positive impact on class-level recovery rates. The impact is economically meaningful: a one standard deviation increase in voting class concentration increases class-level recovery rates by 13 percentage points. When

[26] The identity of the fulcrum class depends on the overall valuation of the firm relative to the total value of outstanding claims. Thus, the fulcrum dummy does not identify seniority, as in some cases senior secured claimants constitute the fulcrum class, while in others it could be the original equity holders.

combined with the fact that higher $t_2$ concentration is negatively related to overall recovery rates, these findings are consistent with the idea that concentrated voting classes bargain for higher recovery rates for themselves at the cost of reducing overall returns for other investors.

In addition, we find that more concentrated fulcrum classes receive significantly lower estimated recovery rates. This is further evidence that highly concentrated classes are able to push negotiations in their favor, as the strategic incentive for investors in the fulcrum class is to push for *lower* estimated recoveries, since this allows them to squeeze out more junior classes and retain all of the equity value of the firm (Gilson Hotchkiss, and Ruback, 2000). Increasing the concentration of the fulcrum class by one standard deviation decreases recovery rates by 20.1 percentage points on net, a 36.4% reduction from the mean recovery received by fulcrum classes. However, as noted above, the concentration of the fulcrum class does not explain the overall negative relationship between ownership concentration and debtor-level recovery rates.

## 2.5. Conclusions

Using a novel dataset covering 136 Chapter 11 bankruptcies, our essay offers a comprehensive view into the concentration of the ownership structure of bankrupt firms, its evolution through bankruptcy, and its influence on Chapter 11 outcomes. In particular, we significantly improve the measurement of ownership concentration, and we are the first to provide empirical insight on trading in bankruptcy, including the role of different institutional types and the fact that in-bankruptcy trading contributes to the consolidation of ownership. We also examine how in-bankruptcy trading ultimately impacts the evolution of the restructuring (through ownership consolidation).

We find that, at the onset of bankruptcy, active investors—asset management firms, hedge funds, and private-equity-affiliated funds—own a relatively small portion of the debt claims of a bankrupt firm as compared to banks and non-financial corporations. Yet, by the time that claimants vote on the Plan of reorganization, active investors (by far, the largest net buyers of claims in bankruptcy) more than double their representation in the firm's capital structure. Furthermore, in bankruptcy, active investors primarily acquire voting claims. Purchasing trade claims in bankruptcy is an important vehicle for the entry of new creditors in bankruptcy, most of which are active investors.

Consistent with Bolton and Scharfstein (1996), we find that firms with more concentrated ownership at the bankruptcy filing are more likely to file with a prearranged bankruptcy plan, pass through bankruptcy more quickly, and are more likely survive bankruptcy as a reorganized entity rather than beng sold or liquidated piecemeal. Firms with more actively traded loans and bonds prior to bankruptcy tend to have more concentrated ownership, while the ownership of firms with more trade debt is typically more dispersed. Finally, using trade as an important source of variation in ownership, we find that increases in the concentration of voting creditors during bankruptcy reduce the speed of restructuring, increase the probability of liquidation, increase class-level recovery rates and decrease overall recovery rates.

The existence of an active market for claims trading during bankruptcy is an important and novel fact to document because ownership concentration is believed to influence bankruptcy costs. In general, a lot of new information is released in bankruptcy. For example, the Schedule of Assets and Liabilities makes public individual holdings of all claimants against the borrower. Ability to transact on this information—i.e., existence of the market in bankruptcy—is therefore likely to enhance efficiency of the bankruptcy process. Furthermore, we establish that trading in bankruptcy significantly increases the concentration of ownership at the time of the vote on the plan of reorganization. Current theoretical literature treats the ownership of a bankrupt firm, and, therefore, negotiations that follow default as static. This is perhaps consistent with the way the bankruptcy process looked through the mid-1990s; however, the dynamics of the bankruptcy process since have changed. The novel facts presented in our essay and evidence of their effect on bankruptcy outcomes change the way we think about ownership as it relates to the restructuring process and highlights the need for further theoretical research on this subject.

# 3

# Can Gambling Increase Savings? Empirical Evidence on Prize-linked Savings Accounts

*This chapter is co-authored with Shawn Cole and Peter Tufano*

## 3.1. Introduction

Personal savings serve as the first available buffer for households when faced with job loss, healthcare costs, or other financial shocks. However, recent survey evidence suggests that a large percentage of households maintain low emergency savings, resulting in high financial fragility. For example, Lusardi, Schneider, & Tufano, (2011) find that nearly half of U.S. households are probably or certainly unable to come up with $2,000 in 30 days, while the FDIC finds that that 29% of U.S. households do not even have a savings account (FDIC, 2012). High financial fragility is not confined to the U.S.; Lusardi et al., (2011) also show that financial fragility is similarly high in the U.K., Germany, and France.[1] Meanwhile, in less-developed countries large portions of the population remain completely unbanked, instead relying on cash and informal groups to provide financial services (Cole, Tufano, Schneider, & Collins, 2008).

[1] Even in the Netherlands, which exhibited the greatest ability to cope with financial shocks of any country in their data, 27% of individuals were certainly or probably unable to come up with €1,500 in 30 days.

Considering these facts, economists and policymakers have investigated many proposals and products aimed at encouraging higher savings rates (see Tufano & Schneider, 2008, for an overview of policy proposals). One such proposal is the usage of prize-linked savings (PLS) products, which provide added excitement to savings by giving participants the chance to win prizes by saving money, typically in a lottery-like setting. While PLS programs have existed for hundreds of years and are prevalent around the world, they have received relatively little academic attention. This essay gives a first look at micro-level data on the usage of PLS accounts, providing evidence on the types of individuals who use PLS and how it affects their overall saving behavior using data from a PLS program run by First National Bank, the third largest banks in South Africa.

PLS accounts differ from standard savings accounts in that they offer a stochastic, heavily-skewed return as opposed to a risk-free flat interest rate. In particular, depositors in a PLS account periodically are entered into a drawing in which their chance at winning a (potentially large) prize is a function of the amount of deposits. This lottery-like system essentially changes the payoff structure for saving, adding an element of risk and, possibly, excitement to holding money in the account.

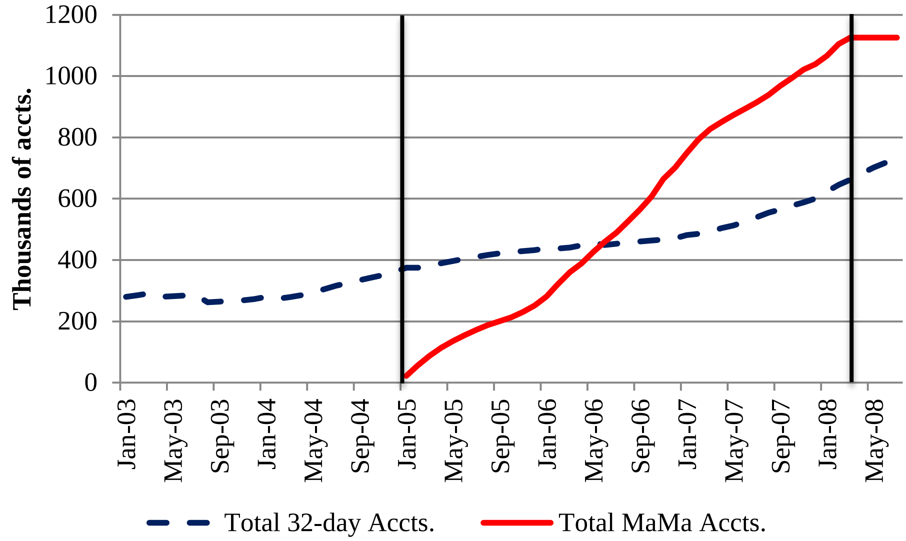
On the other hand, PLS differs from regular lottery gambling by protecting all principal invested. When a consumer places funds in a PLS account, she has access to those funds either on demand or at a future date, and so in this sense she is gambling only with the potential interest payments. Meanwhile, an investment in a lottery ticket can only be regained if the buyer happens to win. Because of this, nearly all lotteries have a negative expected return, while PLS maintains a positive (nominal) expected return.

Given the widespread demand for lottery gambling, it has been hypothesized that the lottery-like incentive structure of PLS could be attractive to large numbers of participants (Kearney, Tufano, Guryan, & Hurst, 2010). Indeed, participation rates in the UK's Premium Bond program, a PLS product, are estimated to be between 22 and 40 percent of UK citizens (Tufano, 2008). The uptake of the PLS account at First National Bank was similarly robust: within 18 months of the start date of the program there were more PLS accounts than regular savings accounts at the bank, and within 3 years PLS deposits amounted to R1.4 billion at the bank, as compared to total savings of R4.5 billion in the comparable standard savings account (Figure 3.1).

In addition to attracting more deposits, the lottery-like structure of PLS also appeals to a different type of saver. Indeed, understanding how PLS users differ from typical savers can shed light on why some individuals struggle to maintain a sufficient level of precautionary savings in standard savings vehicles. Using survey data from individuals that live near First National Bank branches, we find that usage of PLS was especially strong in low- and medium-income areas, and in areas where individuals reported being more severely financially constrained. Corroborating this, we also use account-level data on employees of First National Bank and find that individuals who were the largest net borrowers from the bank were most likely to open a PLS account, while those with moderate savings amounts were least likely. Further, we also find that employees who had no standard deposit accounts previously were 4.9% more likely to open a PLS account than those with accounts. This evidence suggests that PLS could be particularly successful in attracting savings from the set of individuals who are more cash constrained or are completely unbanked, i.e. those individuals who are least likely to maintain emergency savings.

There are at least two reasons why poor and financially constrained individuals might be particularly attracted to PLS. First, it has been hypothesized that lottery gamblers are willing to accept the negative expected return because they are "buying a dream," and they thus gain utility from holding the lottery ticket and dreaming of winning the jackpot (Thaler & Ziemba, 1988). If one supposes that the marginal value of a dream is greater for poorer individuals, or for those individuals with larger debts, then one would predict that these individuals should be more likely to purchase the dream by investing funds in PLS rather than a standard savings account. We find further support for this theory based on self-reported levels of optimism by individuals that live near bank branches. Our evidence shows that branches in areas where a high percentage of individuals report feeling pessimistic and hopeless had especially high uptake of PLS accounts, even after accounting for other socio-economic factors in the area. This suggests that users of PLS are not putting money into their accounts due to over-optimism, but rather because the value of the fantasy of winning the prize money is greater for depressed individuals.

*Panel A: Total number of 32-day and MaMa accounts, bank-wide (thousands of accounts)*




*Panel B: Total deposits in 32-day and MaMa accounts, bank-wide (Rand billions)*

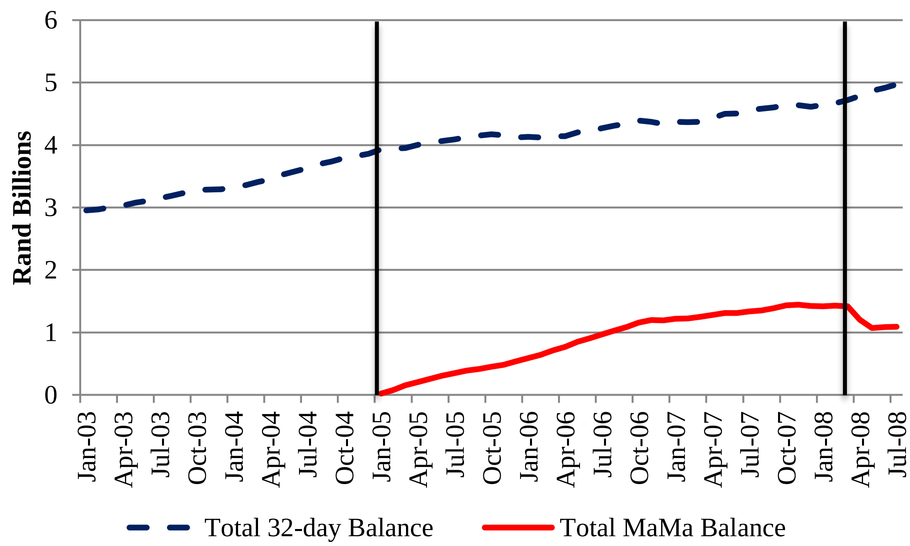



**FIGURE 3.1 - GROWTH OF THE MAMA PROGRAM**

Panel A shows the total number of standard 32-day notice accounts and MaMa prize-linked accounts at First National Bank from January 2003 – July 2008, while Panel B shows the total balances held in these accounts (in Rand billions). In both charts, the vertical lines identify the beginning and end of the MaMa program, in January 2005 and March 2008, respectively.

A second theory of lottery demand is that some consumption is indivisible and therefore an individual might need a large prize in order to materially improve his socioeconomic position or make some large, needed purchase. For example, one cannot purchase half of a car or TV. For an individual who needs a large sum of money either for a large purchase or to pay off large debts, earning small amounts of risk-free interest in a standard savings accounts may not be nearly as attractive as the prospect of winning a large prize in a PLS. Our findings are also consistent with this idea.[2]

An important issue in evaluating PLS is whether these types of accounts can actually attract new savings or if they just cannibalize regular savings. Using account-level data, we show that employees who open a PLS account tend to increase their net savings at First National Bank by about 1% of their income. Splitting bank employees by their net financial position prior to opening a PLS account, we find that both savers and borrowers who use a PLS account increase their total savings at the bank relative to those who do not open a PLS account, with net borrowers increasing their savings the most. Importantly, individuals who opened PLS accounts also tended to increase savings in the bank's standard savings account, suggesting that the funds placed in PLS were not simply shifted from regular savings. Further, we show that demand for the PLS program nationwide was especially strong in periods when the jackpot of the South Africa National Lottery was small, suggesting that PLS and lottery gambling acted as substitutes. Taken together, these findings show no evidence that PLS cannibalizes regular savings, and instead establish that at least some of the increases in savings comes as result of reduced expenditure on lottery gambling.

A unique feature of PLS is the fact that certain lucky account holders periodically win prizes. In the PLS program run by First National Bank, each month a total of 113 prizes were awarded, including a grand prize of R1,000,000 and R500,000 in smaller prizes. We track the accounts of these randomly selected prize-winners and test whether they are more likely to close their accounts after winning, or whether winning a prize induces them to invest more in PLS. Relative to non-winners, winners of small R1,000 prizes are 4.2% more likely to close their accounts within one year of winning their prize, while winners of larger prizes are no more likely to close their accounts. Conditional on keeping the PLS account open, however, prize winners keep substantially more in their accounts than those who did not

[2] While our data do not allow us to separate these two hypotheses of demand for PLS, it is important to note that Blalock, Just, & Simon, (2007) find evidence that the poor view lottery play more as an investment and less as entertainment. If this is the case, PLS should be particularly attractive to those poorer individuals as it provides the same skewed returns without the loss of principal.

win prizes. In many cases, prize winners increase their account balances in PLS by more than the amount won, indicating that this increased investment in PLS is more than just a wealth effect. This increased savings is persistent for at least year after winning.

We also find that large prize winners create a “buzz” that generates more demand for PLS in the local area. In particular, bank branches which have a R1,000,000 prize winner experience 11.6% excess growth in PLS deposits in the month after the win, relative to all other bank branches. Thus, the excitement of winning a prize has spillover effects that also serve to increase savings by other individuals.

This essay connects to a broad literature that investigates financial innovations that help individuals save more, such as default options (Carroll, Choi, Laibson, Madrian, & Metrick, 2009), commitment devices (Ashraf, Karlan, & Yin, 2006; Thaler & Benartzi, 2004), or simply reminding individuals to save (Karlan, McConnell, Mullainathan, & Zinman, 2012). Our essay adds to this research by providing a first micro-level look at the usage and consequences of prize-linked savings. In particular, our findings provide insight into a number of questions raised by previous research on PLS. In their overview of PLS, Kearney et al., (2010) state that, “the key question yet to be answered is whether the availability of prize-linked savings would generate new savers and new saving, and if so by whom.” Our evidence suggests that PLS can indeed attract new savers and new saving, and that, relative to typical savings accounts, PLS is particularly attractive to cash constrained and poorer individuals. This confirms anecdotal evidence that PLS is especially successful with low-income depositors (Guillén & Tschoegl, 2002) and is in line with previous research that has shown that lottery demand is particularly strong for disadvantaged members of society (for an overview of this research, see Herring & Bledsoe, 1994). Our findings also build on Atalay, Bakhtiar, Cheung, & Slonim (2012) who use an online experiment to show that PLS tends to reduce lottery expenditure while increasing total savings. Our findings are directly in line with this evidence. This suggests that, while PLS likely has both savings and gambling elements (Tufano, 2008), most participants reduce lottery spending rather than regular savings in order to invest in PLS. Finally, our findings are relevant to Lusardi et al. (2011), who find that gamblers are particularly prone to lack precautionary savings. By combining a gambling element with savings, PLS provides a natural way for these individuals become less financially fragile.

The remainder of the chapter is organized as follows. Section 3.2 gives background information on First National Bank's PLS product and the data available for analysis. Section 3.3 provides results on the characteristics of PLS participants, while Section 3.4 presents evidence on whether PLS reduces deposits in regular savings products or in the amount of lottery gambling. Section 3.5 then discusses how winning a prize affects both the prize winner and others nearby. Section 3.6 concludes.

## 3.2. Background and Data

### *3.2.1. First National Bank's Prize-Linked Savings Product*

There are relatively few banks serving South Africa's population of 44.8 million.[3] The South African Reserve Bank (2008) lists only 17 total banks functioning in South Africa in 2008, of which the four largest (the "big four") account for 91% of total assets. First National Bank is the retail and commercial bank subsidiary of FirstRand Bank Limited, the third largest bank in the country.

First National Bank introduced a PLS account in January, 2005 in an effort to expand its deposit base among low-income and unbanked individuals (see Cole et al., 2008, who also discuss the informal savings programs that exist in South Africa). First National called its PLS account the "Million-a-Month Account," or MaMa, and awarded a grand prize of R1,000,000 to one random account-holder each month. In addition to the grand prize, the bank initially also awarded two prizes of R100,000, 10 prizes of R20,000, and 100 prizes of R1,000 each month. In September, 2007, the bank doubled the number of smaller prizes given each month, awarding four R100,000 prizes, 20 R20,000 prizes, and 200 R1,000 prizes.[4] Throughout the program, each account-holder received one entry into the lottery for each R100

[3] South Africa Census, 2001.

[4] For reference, on January 1, 2005, the exchange rate was R6.36 South African Rand to $1 U.S. dollar, and the median annual income in 2008 was R45,002.

held in his account.[5] MaMa accounts were 32-day notice accounts, meaning that if a customer wished to withdraw some of her funds she must notify the bank 32 days in advance of the withdrawal.[6] The most comparable account at First National to MaMa was a standard 32-day notice account, which paid interest on a variable scale depending on the customer's balance in the account. As of November, 2004, for balances below R10,000 the 32-day account paid 4% annual interest, for balances between R10,000 and R25,000 it paid 4.25% APR, and for balances from R25,000 to R250,000 the APR ranged from 4.5% to 4.75% (Cole, et al., 2008).[7]

In contrast to the regular 32-day account, the implied interest rate paid on MaMa balances depended completely on the amount of deposits held in the accounts. As the number of participants increased, the expected interest rate decreased because each account-holder then had a lower chance of winning a prize. The new MaMa accounts proved to be quite popular, and deposits increased dramatically in the first months (Figure 3.1). Indeed, although the total amount held in MaMa accounts never approached the aggregate balance of the regular 32-day accounts, the number of MaMa accounts exceeded that of regular 32-day accounts by June 2006, a mere 18 months after the product was launched. Because of this growth, the expected interest rate on MaMa accounts declined rapidly. When the first drawing was held, in March 2005 (three months after the start date of the program), the expected annualized interest rate for holding R100 in a MaMa account was about 12.2% due to the relatively small number of accounts. However, as the popularity of the program grew the expected return quickly dropped and by November 2005 the rate was 3.81%, lower than that offered by the regular 32-day account. At its lowest, the expected interest rate on MaMa accounts was 1.33%, in August 2007, just before the number of prizes was doubled.[8]

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[5] Initially, the accounts paid no interest at all, but at a later date the bank began paying a 0.25% interest rate on deposits in addition to the random prizes.
[6] 32-day notice accounts are common in South Africa and are offered by all of the major banks there.
[7] The inflation rate in South Africa in November 2004 was 3.3%, implying that the real interest rates for the various balance levels were 0.7%, 0.95%, and 1.2% - 1.45%.
[8] The average inflation rate in South Africa during the sample period was 5.4%, meaning that in expected terms MaMa participants were earning negative real returns.

The MaMa program only lasted until March 2008, when it was deemed a violation of the Lottery Act of 1997 by the Supreme Court of Appeals (FirstRand Bank v. National Lotteries Board, 2008). In South Africa, as in the U.S., the government holds a monopoly on lotteries that are run for profit. Although First National argued that its program wasn't technically a lottery, since all principal was preserved, it failed to convince the courts and was forced to end the program. At the end of March, all MaMa accounts were converted to regular 32-day accounts, and account holders were allowed to withdraw their deposits if they chose to do so. The data provided by First National ends in July 2008, four months after the program ended. During that time period, aggregate MaMa balances fell 16.2% in April 2008, and an additional 11.8% in May. However, balances held steady in June and July, at which point our data end. Thus, while some participants in the program did withdraw their funds, over 77% of all PLS deposits remained in the bank for at least four months after the accounts converted to standard savings products.

### *3.2.2.Data*

Most of the data for this chapter comes directly from First National Bank, who provided us with three main datasets: branch-level data for all bank branches, account-level data for all bank employees, and account-level data for all prize winners. In addition, we use data from the 2005 FinScope financial survey of South Africa, provided by FinMark Trust. Details of each dataset are described below.

#### *3.2.2.1. First National Bank Data*

First National provided both branch-level and account-level data for this chapter. At the branch level, we have monthly observations for each of 661 bank branches from January 2003 through July 2008. For each month, we observe the total number of accounts and total Rand balance held at the branch in both standard 32-day accounts and MaMa accounts. Table 3.1 provides summary statistics of the total number of accounts and total deposits at each branch as of March 2008, when the MaMa program ended.

In addition to branch-level time series data, we also observe branch-level demographic characteristics of depositors in both 32-day and MaMa products for one snapshot taken in June 2008, 3 months after the MaMa program ended. This allows us to compare the characteristics of MaMa

## TABLE 3.1
## SUMMARY STATISTICS OF FIRST NATIONAL BANK DATA

This table reports summary statistics for data obtained from First National Bank. Panel A presents summary statistics on the total number of accounts and total deposits in standard 32-day and MaMa accounts at 604 bank branches as of March 2008, when the MaMa program ended. Panel B compares the share of balances owned by race and gender for 32-day and MaMa accounts. Panel C contains account-level summary statistics for bank employees.

*Panel A: Branch-level summary statistics as of March 2008*

| | *Product* | *N* | *Mean* | *Std. Dev.* | *10th percentile* | *Median* | *90th percentile* |
|---|---|---|---|---|---|---|---|
| Total No. of Accounts | 32-day | 604 | 1,097 | 1,064 | 148 | 826 | 2,273 |
| | MaMa | 604 | 1,863 | 2,505 | 211 | 1,408 | 3,797 |
| Total balance (Rand millions) | 32-day | 604 | R 7.81 | R 8.08 | R 0.89 | R 5.29 | R 18.00 |
| | MaMa | 604 | R 2.35 | R 3.25 | R 0.23 | R 1.70 | R 5.00 |

*Panel B: Share of balances owned by race and gender*

| | MaMa | 32-day |
|---|---|---|
| Race: | | |
| Black | 0.45 | 0.45 |
| White | 0.37 | 0.41 |
| Asian | 0.09 | 0.07 |
| Mixed race | 0.08 | 0.07 |
| | | |
| Males | 0.52 | 0.46 |

*Panel C: Account-level summary statistics of bank employees as of March 2008*

| | | | | | | | *% with non-zero balance* | |
|---|---|---|---|---|---|---|---|---|
| | *N* | *Mean* | *Std. Dev.* | *$10^{th}$ %tile* | *Median* | *$90^{th}$ %tile* | *Jan. 2005* | *Mar. 2008* |
| Total balance: | | | | | | | | |
| 32-day saving | 38,301 | 872.11 | 9,989 | 0 | 0 | 322 | 9.9% | 15.4% |
| Money market | 38,301 | 3,285.32 | 31,091 | 0 | 0 | 841 | -- | 22.9% |
| Cheque | 38,301 | 206.12 | 17,507 | -5,833 | 0 | 2,703 | 39.0% | 62.6% |
| MaMa | 38,301 | 566.81 | 5,510 | 0 | 0 | 723 | 5.5% | 45.5% |
| Combined | 38,301 | 4,930.35 | 39,921 | -5,065 | 0 | 10,043 | 41.4% | 77.9% |
| Income Estimate | 38,301 | 175,920 | 203,408 | 60,000 | 112,297 | 360,000 | -- | -- |
| *Combined bal. (% income)* | 38,301 | 0.035 | 0.67 | -0.04 | 0 | 0.07 | -- | -- |

participants to those of typical savers, which we do in Table 3.1. Separating by race, MaMa depositors are less likely to be white, and more likely to be Asian or of mixed race.[9] Looking at gender, men account for a total of 52% of MaMa deposits, as compared to only 46% of regular 32-day deposits, suggesting that the lottery payoff structure might be more attractive to men than women, perhaps due to lower risk aversion (Eckel & Grossman, 2008) or overconfidence (Barber & Odean, 2001). MaMa participants also tended to be younger than standard 32-day account holders (Figure 3.2, Panel A). This is important, as younger individuals also tend to be those who maintain less precautionary savings (Lusardi et al., 2011).[10]

The income profile of MaMa savers appears to be quite similar to that of regular savers (Figure 3.2, Panel B). In fact, those in the lowest income bracket account for a slightly larger share of total 32-day balances (45%) than of MaMa balances (42%). While some of the evidence in Section 3.3 suggests that the MaMa product had more demand in lower-income areas, it should be kept in mind that overall it does not appear that MaMa savings came disproportionately from low-income households.

In addition to the relatively coarse branch-level data, we also analyze account-level data for employees of First National Bank. This dataset contains month-by-month information on account balances of 38,256 employees of First National Bank for the time period from January 2005 - March 2008. For each employee, we observe the month-end balance of their 32-day savings, cheque, money market[11], and MaMa accounts. In addition, we also have a snapshot of the employee's race, gender, age, income estimate[12], and the region of South Africa in which they work. Summary statistics of employee account balances are provided in Table 3.1, Panel C.

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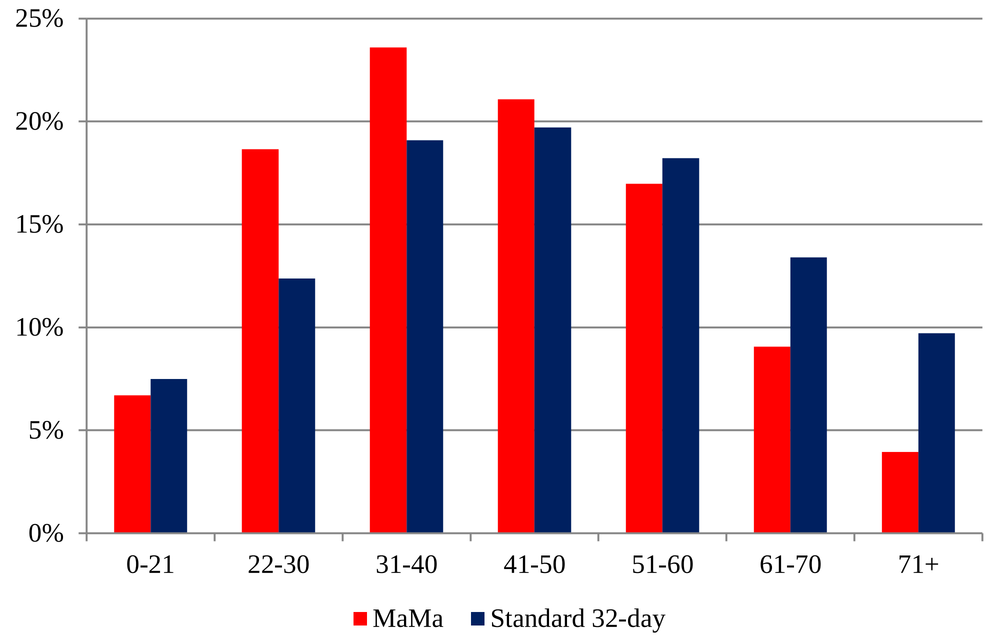
[9] Black persons are those of native African descent. Asian persons include those of Indian descent.
[10] In addition, if PLS products can be used to develop a habit of saving earlier in life, the long-term benefits could be multiplied through compound interest.
[11] The money market account was a special account available only to staff of the bank that was launched in July 2007, towards the end of the sample period.
[12] Income data was not directly available from First National and was instead estimated by the bank according to an internal model.

*Panel A: Share of deposits held, by age bracket*




*Panel B: Share of deposits held, by income bracket*

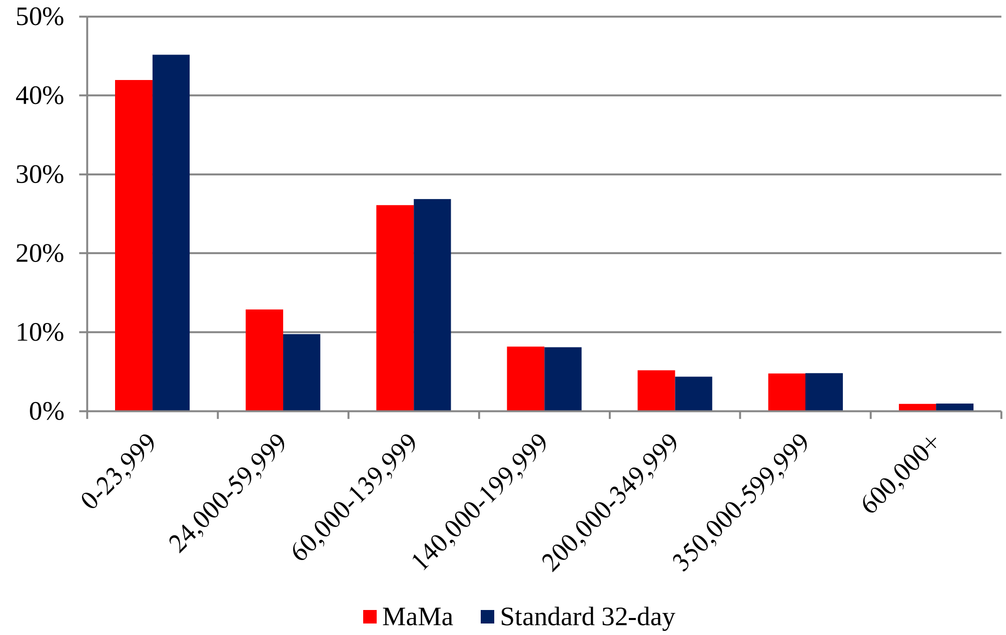



**FIGURE 3.2 - SHARE OF DEPOSITS HELD IN STANDARD SAVINGS AND PLS, BY AGE AND INCOME**

Panel A of this figure displays share of total deposits held by individuals in different age brackets for both standard 32-day and MaMa accounts. Panel B shows the share of total balances held by individuals across income brackets. Data reflect account balances as of June 2008, 3 months after the MaMa program ended.

Of the 38,256 employees, 12,237 were terminated as of December 2008, when the data was gathered. In all regressions, we include an *ex-staff* dummy to control for these individuals, but our results are unchanged if these individuals are removed completely.

There are both advantages and disadvantages to working with staff data. It is most likely true that the majority of First National employees do most or all of their banking at First National due to familiarity with the products, the ease of banking where you work, and possible pressure from managers to use the products. Thus, by focusing on staff data, we can observe a more comprehensive view of MaMa participants' saving and borrowing behavior after opening a MaMa account. However, to the extent that the staff of the bank is not a representative sample of the South African population, it is possible that our results are not externally valid. For example, only 41% of bank employees are black as compared to 73% in the population at large. Of more particular concern is the fact that bank employees are likely better educated and earn more than the population in general. The average First National employee earns R175,963 per year, while in 2006 average household income in South Africa was estimated to be R74,589 (Statistics South Africa, 2008). Finally, just over 20% of the staff in our sample have no cheque, money market, 32-day, or PLS account. Nationwide, about 47% of individuals were completely unbanked in South Africa in 2005. To the extent possible, we control for staff characteristics in our analysis, but we do note that there are large differences between the staff sample and the general population.

An important aspect of the staff data is that it contains information on cheque account balances, which are often negative. The reason for this is that it is easier for staff to obtain permanent overdraft facilities through their cheque accounts than to obtain a credit card or personal loan from the bank. Thus, these negative balances can be interpreted as unsecured consumer credit obtained from the bank. Table 3.1 shows that a significant number of bank staff have negative balances in their cheque accounts. Net of these negative balances, the average employee had about R4,930 in savings across all accounts at the bank in March 2008, or about 3.5% of their annual income. A total of 29% of employees are net borrowers from the bank, while just over 22% have no active accounts at the bank at all. Further, there are a few employees with extremely large amounts held in their accounts, or extremely high levels of borrowing. In all of our analysis using the staff dataset, we winsorize account balances at the 1% and 99% levels to prevent undue influence of these outliers.

Finally, we also have account-level information on prize winners. In the winners dataset we have month-by-month information on MaMa account balances and demographic information only; account balances in other products was not provided. In total there were 4,965 prizes given out to 4,341 account holders (some account holders won more than once) between March 2005, when the first drawing was held, and March 2008, when the program closed. By merging the winners data to the branch time series data, we can verify that the awarding of prizes was indeed random by comparing the total actual prizes awarded by branch to the expected prizes (calculated based on the total value of MaMa accounts held at the branch compared to bank-wide MaMa account holdings). Figure 3.3 shows that the actual and expected prizes match up very closely.

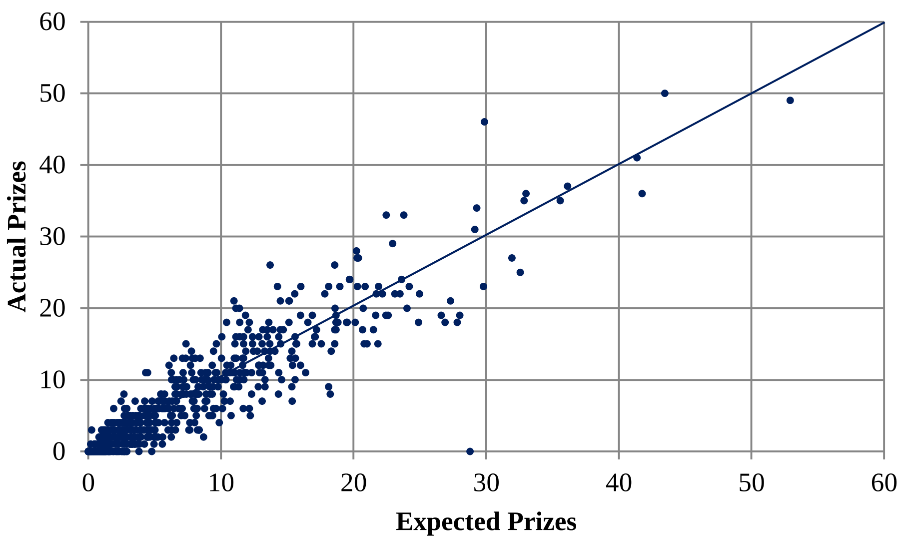



**FIGURE 3.3 - EXPECTED VS. ACTUAL NUMBER OF PRIZES AWARDED PER BRANCH**
This figure compares the actual number of prizes awarded to account holders at a particular branch to the expected number of prizes. The expected number of prizes is calculated as the share of total MaMa deposits held at the branch in a given month multiplied by the total number of prizes awarded in that month. The total number of actual and expected prizes is then summed across the 36 months of the MaMa program for each branch to get total actual and expected prizes. If all branches had drawn exactly their expected number of prizes, points would line up exactly on the displayed 45-degree line.

#### 3.2.2.2. *FinScope Data*

We augment the data obtained from First National Bank with geographic, demographic, and socioeconomic data collected in the 2005 FinScope Survey. FinScope surveys are nationally representative surveys carried out annually by FinMark Trust, and are designed to measure the use of financial products by consumers in South Africa. The 2005 survey contains responses from 3,885 individuals, and has in-depth information on each respondent's financial sophistication, use of financial products, attitudes towards financial service providers, income and employment status, demographic information, and indicators of their general well-being.

We relate these characteristics to MaMa demand at individual First National Bank branches by taking average responses of individuals who live near each branch. Specifically, we use the latitude and longitude of each bank branch and the latitude and longitude of the center of the city or town of each FinScope respondent to measure the distance between the two locations using the Haversine formula. For each branch, we average the values for all respondents within a 50km (31.1 miles) radius of the branch, thereby giving the general characteristics of individuals who are likely to use that particular bank branch.

Table 3.2 provides summary statistics of the collapsed survey data at the branch level. For 62 of the bank branches there were no survey responses with 50 km, so the number of observations drops to a total of 542 branches.[13] Of particular note is the high share of individuals with no bank accounts at all (49%) as well as very elevated unemployment rates (25%).

In the analysis in Section 3.3, we will correlate FinScope's Financial Segmentation Model (FSM) with demand for MaMa. The FSM places individuals in one of eight tiers based on answers to a set of questions in the survey. The model is made up of five components, each of which is meant to capture a specific aspect of each individual's access and use of financial services, along with how people manage their money and what drives their financial behavior:

[13] Results are similar if we use a radius of 30km (18.6 miles) or if we limit to branches that had at least 15 respondents within a 50km radius. Sample size is reduced to 492 branches in the first case, and 463 branches in the second, so statistical significance is reduced somewhat for some estimates in these robustness checks, but estimated signs and magnitudes are similar.

- Financial penetration: take-up of available financial products
- Financial access: physical access to financial services
- Financial discipline
- Financial knowledge
- Connectedness and optimism: individual's overall feeling of fulfillment, of being connected to their community, and of having hope of achieving their lifetime goals[14]

The respondent's combined score across these five categories is used to segment the population in eight tiers, with higher tiers signifying individuals who have more uptake and access to financial products, more financial discipline and knowledge, and feel more connected and optimistic.

In addition to FinScope's FSM tiers, we also construct our own indices of characteristics that might affect demand for PLS. These indices are based directly on questions that ask about individual's attitudes towards risk, their financial knowledge, and how financially constrained the individual is. Detailed information on how these indices were created is provided in Section 3.3, where we use them to analyze demand for the MaMa product.

### 3.3. Uptake of MaMa

The widespread growth of MaMa was remarkable. By June 2008, the number of MaMa accounts at First National Bank exceeded the number of 32-day savings accounts at First National for every age, gender, income, and race subgroup.[15] Among employees of the bank, just 27% used a regular 32-day savings account (defined as having had a positive balance for at least one month) during January 2005 - March 2008, while 63% opened a MaMa account during the sample period. Why was MaMa so popular? In this section we analyze the characteristics that are associated with opening a PLS account using both FinScope survey data as well as account-level data of First National employees. Knowledge of what drives demand for PLS can help academics and policymakers alike understand how consumers think about savings and gambling, as well as assess the potential for PLS to encourage precautionary savings.

[14] For more information on the FSM and how it is calculated, see the FinScope 2005 brochure at http://www.finscope.co.za/documents/2005/SA05_brochure.pdf.
[15] However, average account balances were much lower in MaMa accounts than regular 32-day savings.

## TABLE 3.2
## FINSCOPE SUMMARY STATISTICS

This table reports summary statistics of demographic characteristics derived from the FinScope 2005 survey. Each item represents the mean or median of all survey respondents within 50km of each bank branch. This table reports summary statistics across the distribution of the 542 branches which had any respondents within the 50km radius. Financial segmentation model (FSM) tier and FSM components are calculated by FinScope based on responses to a battery of questions. Each respondent is segmented for each component separately on a scale from 1 to 8, and then the overall tier is a combination of those components (and also ranges from 1 to 8). For all components a higher tier signifies more, e.g. higher financial penetration score signifies that an individual has adopted more financial products. The constructed indices are also derived from FinScope survey questions but are constructed by the authors explicitly to test theories of PLS demand. These indices are described in detail in the text.

| | *N* | *Mean* | *Std. Dev.* | *10th %tile* | *Median* | *90th %tile* |
|---|---|---|---|---|---|---|
| *Demographics* | | | | | | |
| Race: | | | | | | |
| Black | 542 | 68.72% | 26.30% | 33.72% | 72.26% | 100.00% |
| White | 542 | 15.25% | 13.59% | 0.00% | 16.24% | 25.60% |
| Asian | 542 | 3.10% | 7.13% | 0.00% | 1.01% | 8.21% |
| Mixed race | 542 | 12.93% | 22.48% | 0.00% | 4.15% | 40.69% |
| % Male | 542 | 48.74% | 3.29% | 47.20% | 48.83% | 50.51% |
| % Married | 542 | 42.47% | 12.59% | 29.19% | 45.33% | 50.88% |
| Median Age | 542 | 33.76 | 5.60 | 27 | 32 | 37 |
| Median Household Income | 542 | 29,983 | 18,313 | 15,000 | 27,000 | 42,000 |
| % Rural | 542 | 30.75% | 33.78% | 0.75% | 14.39% | 90.52% |
| % with at least High School Education | 542 | 39.73% | 15.86% | 16.65% | 39.91% | 55.84% |
| % unemployed | 542 | 25.28% | 10.58% | 16.41% | 22.96% | 38.92% |
| Homeownership rate | 542 | 74.36% | 14.86% | 64.84% | 73.31% | 93.40% |
| *Financial Indicators* | | | | | | |
| % Banked | 542 | 50.91% | 17.04% | 28.05% | 54.70% | 67.63% |
| FSM Tier | 542 | 3.45 | 0.76 | 2.41 | 3.54 | 4.15 |
| FSM Components: | | | | | | |
| Financial Penetration | 542 | 2.28 | 0.56 | 1.61 | 2.35 | 2.96 |
| Financial Access | 542 | 3.85 | 0.99 | 2.51 | 3.99 | 4.73 |
| Financial Discipline | 542 | 4.94 | 0.42 | 4.45 | 4.99 | 5.27 |
| Financial Knowledge | 542 | 3.47 | 0.60 | 2.63 | 3.53 | 4.08 |
| Connectedness and Optimism | 542 | 6.68 | 0.32 | 6.29 | 6.75 | 6.98 |
| Constructed indices: | | | | | | |
| Risk index | 542 | 0.95 | 0.21 | 0.65 | 0.97 | 1.16 |
| Financial knowledge index | 542 | 0.56 | 0.61 | -0.25 | 0.76 | 1.07 |
| Financial constraint index | 542 | 1.43 | 0.31 | 1.11 | 1.43 | 1.82 |

*3.3.1. Geographic characteristics and MaMa demand*

Because of its lottery-like payoff, it has been hypothesized that PLS might be attractive to low-wealth individuals, those with less education, or perhaps to particular racial groups, since it is known that individuals with these characteristics typically spend a larger percentage of their income on lottery gambling (Kearney et al., 2010). We test these intuitions by correlating uptake of the MaMa product at each bank branch to demographic and socioeconomic characteristics of individuals who live within 50 km of the branch, using responses to the 2005 FinScope survey. Panel A of Table 3.3 presents OLS regressions which relate overall MaMa uptake at a particular branch with demographic characteristics of individuals who live near the branch. In these regressions, the dependent variable is either the total balance held in MaMa accounts at the branch or the total number of MaMa accounts as of March 2008. To determine whether demand for MaMa products differs from the demand for regular 32-day savings, we control for the total balance held in 32-day savings accounts as well as the square of this number at each branch, or the total number of accounts and its square in the second column.[16] We also control for whether the branch is located in a rural area to account for branch size differences.

Confirming the intuition that large prizes are most attractive for low-income households, we find a negative relationship between median income and MaMa demand. We estimate that a one standard deviation decrease in median income (a reduction of R 18,313 per year) would increase total balances held in MaMa accounts by R 184,658 at a branch, or a 7.6% increase from the mean balance held at each branch. While this finding is in line with intuition of demand for lottery products by low-wealth individuals, it is not entirely consistent with the results presented in Panel B of Figure 3.2, which shows that MaMa balances did not come disproportionately from lower-income households. We return to this issue with more evidence below in Section 3.3.2.

[16] Similar results are found if the dependent variable is defined as the ratio of MaMa balances to savings balances instead of including the total savings balance as a right-hand side variable.

# TABLE 3.3

## FINSCOPE CHARACTERISTICS AND MAMA DEMAND

This table presents results of OLS regressions where the dependent variable is the total usage of MaMa in March 2008 (at the close of the program) for each bank branch. Panel A shows the relationship between demographic characteristics and MaMa usage, as measured both by total MaMa deposits (in Rand thousands) and the number of MaMa accounts. Panel B adds financial characteristics to these demographic controls to test whether banking attitudes have an additional impact on MaMa usage. To be concise we present only results relating to total MaMa deposits in Panel B, but similar results are found using number of MaMa accounts. Independent variables come from the FinScope 2005 survey, and are averages (or medians, if specified) of the variables for all respondents withing a 50km radius of the bank branch. *FSM Tier* is a classification created by FinScope which categorizes respondents by various financial segments, and is based on 5 separate components which are identified separately in Panel B. In Panel B we also create our own indices based on responses to the FinScope survey which focus on three possible drivers of MaMa usage: high risk tolerance, a lack of financial knowledge, or the presence of financial constraints. See text for a complete explanation of how the FSM tiers and our constructed indices were created. In all regressions we control for the size of the branch by including the total amount of regular 32-day deposits and the square of this value as independent variables. Standard errors are clustered by 54 district municipalities, and are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

*Panel A: Demographic characteristics*

| *Dependent variable:* | *MaMa deposits* | *No. of MaMa accts.* |
|---|---|---|
| Race (% mixed race omitted): | | |
| % Black | -270.150 | -363.552 |
| | (390.410) | (307.986) |
| % White | 493.976 | 36.268 |
| | (646.400) | (518.915) |
| % Asian | 1,757.335 | 3,410.286** |
| | (1,640.562) | (1,501.422) |
| % Male | -246.534 | 462.912 |
| | (1,146.687) | (1,185.337) |
| % Married | -675.170 | -758.057 |
| | (592.684) | (628.073) |
| Median Age | -23.171** | -6.742 |
| | (11.200) | (9.983) |
| Median Household Income | -0.121*** | -0.069** |
| | (0.039) | (0.034) |
| % with at least High School education | 553.235 | -335.191 |
| | (568.926) | (520.268) |
| Unemployment rate | -674.844 | -114.702 |
| | (654.885) | (721.396) |
| Homeownership rate | -736.703 | -546.040 |
| | (449.187) | (358.113) |
| Rural Area | -1,035.365*** | -706.019** |
| | (268.962) | (284.348) |
| | | |
| Observations | 542 | 542 |
| *R*-squared | 0.690 | 0.590 |

**TABLE 3.3 -** *continued*

*Panel B: Financial characteristics*

| *Dependent variable:* | *MaMa deposits(Rand thousands)* | | | |
|---|---|---|---|---|
| % banked | 305.404 | | | |
| | (466.952) | | | |
| FSM Tier | | -30.997 | | |
| | | (178.091) | | |
| FSM Components: | | | | |
| Financial Penetration | | | -138.219 | |
| | | | (342.816) | |
| Financial Access | | | 49.160 | |
| | | | (137.817) | |
| Financial Discipline | | | 40.116 | |
| | | | (162.557) | |
| Financial Knowledge | | | 152.047 | |
| | | | (217.671) | |
| Connectedness and Optimism | | | -530.134*** | |
| | | | (176.995) | |
| Constructed indices: | | | | |
| Risk Index | | | | 640.898** |
| | | | | (282.530) |
| Financial Knowledge Index | | | | -115.163 |
| | | | | (153.215) |
| Financial Constraint Index | | | | 401.560*** |
| | | | | (142.612) |
| Demographic controls | Y | Y | Y | Y |
| Observations | 542 | 542 | 542 | 542 |
| *R*-squared | 0.690 | 0.690 | 0.695 | 0.695 |

In addition to the relationship between income and MaMa demand, we also find that areas with younger individuals tend to have higher MaMa demand. In particular, reducing the median age by one standard deviation (5.6 years) is associated with an increase of R 129,644 in MaMa deposits, a 5.3% increase from the mean. Contrary to expectations, we find little to no relationship between race or education and MaMa demand. However, when we measure MaMa demand by the number of accounts rather than total account balances (Panel B of Table 3.3), we do find that areas with higher Asian populations tend to have higher usage of MaMa.

Panel B of Table 3.3 tests whether additional financial characteristics are associated with MaMa demand. To be concise, here we only present results where the dependent variable is the total amount of MaMa deposits, but results are similar if the number of MaMa accounts is used instead. In this panel, we fail to find evidence that uptake of MaMa was higher in areas with more unbanked individuals. In the next two columns, we use FinScope's Financial Segmentation Model as an independent variable and test its association with PLS demand. The FSM categorizes individuals according to their financial access, knowledge, discipline, and usage of financial products, as well as their overall optimism and connectedness. When we simply include the average overall FSM tier for the area we again fail to find a strong relationship between FSM and MaMa demand. However, when we split the FSM by its components, we find that the only strong predictor of MaMa usage is low levels of optimism and connectedness.

The optimism and connectedness FSM score is derived from a set of survey questions that are designed to measure an individual's satisfaction with their life, how hopeful they are of reaching their life dreams, and how connected they feel to others around them.[17] In some ways, it is unsurprising that this is the only FSM component that shows a significant relationship to MaMa usage, as all of the other components are likely highly correlated with the demographic controls already included in the regressions. However, it is striking that it is areas in which individuals feel *least* hopeful that we see the highest usage of the MaMa product. This suggests that demand for PLS is likely not driven by over-optimism or overweighting of low probabilities, but rather by depressed or pessimistic individuals who are "buying a dream" by depositing some funds in the MaMa account. This finding is also related to recent evidence from the Consumer Federation of America & The Financial Planning Association (2006), which found that 21% of Americans, and 38% of those with incomes below $25,000, think that winning

[17] For example, respondents are asked whether they agree with statements such as, "I have many dreams in life but will never achieve them," "My life has meaning and purpose," "I feel lonely," and "In many ways, my life is ideal."

the lottery represents the most practical way for them to accumulate several hundred thousand dollars. Individuals who feel that their dreams are extremely difficult to reach may very well feel like the only way possible for them to even have a chance at reaching those goals is by winning a large prize. PLS differs from standard savings accounts by providing just such a skewed incentive structure.

In the final column of Panel B, we construct three indices to directly test three theories of lottery demand. Each index is constructed by adding up the share of individuals who live near a branch that fit into particular categories. First, we create a measure of the attitudes toward risk of individuals near each bank branch by adding the share of respondents who:

- Agreed with the statement, "To get ahead in life, one needs to take some risks"
- Felt that there were no factors (e.g. flood, theft, or death) that could impact their finances
- Had money invested in the stock market
- Had money invested in an entrepreneurial venture[18]

A higher risk index score is designed to indicate areas where individuals are more willing to take on risks, or do not perceive as many risks. Since the random payoff of PLS is substantially more risky than that of a standard savings account, one would expect that more risk-tolerant individuals would be more attracted to PLS. Second, we create a financial knowledge index by adding up the share of respondents who:

- Have any kind of savings account
- Report having "a good idea of the interest rate they get on the money they save"
- Feel they "know quite a bit about money and finance"
- Use a budget

From this amount, we subtract the share of respondents who:

- Report that they "don't understand how banks work"
- Would like education on how interest rates work
- Would like education on how to save more money
- Feel out of control of their finances

[18] For example, if within a 50km radius of a bank branch 60.5% of individuals agree that to get ahead in life you need to take risks, 28.8% do not perceive any factors that could impact their finances, 1.6% invest in the stock market and 2.1% invest in entrepreneurship, the total risk index for that branch would equal 0.605 + 0.288 + 0.016 + 0.021 = 0.930.

This index is designed to capture the amount of general financial knowledge that individuals feel they have in the area. Finally, we construct a financial constraint index by adding up the share of respondents who:

- Report being unbanked because they either have no income or no money
- Report having a hard time keeping up with their debts
- Have borrowed money to buy food in the past
- Report that they have often or sometimes go without food in the past 12 months

To this amount we also add the average share of income that is spent on necessities for respondents near the bank.

These three indices are designed to test whether PLS demand is correlated with three factors that could drive demand for PLS. Namely, one would predict that individuals who have higher risk tolerance would be relatively more attracted to PLS than risk-free savings accounts. Second, we hypothesize that individuals with less financial knowledge might be more attracted to PLS since the chance at winning a large prize is easier to comprehend than compound interest (Lusardi & Mitchell, 2007; Stango & Zinman, 2009). Lastly, we predict that individuals that report tighter cash constraints will have higher demand for PLS, since PLS represents a chance to dramatically change their lives while only needing to deposit a small amount of their scarce resources. This theory has been proposed as an explanation of lottery play by poorer individuals (Ng, 1975) and has also been suggested as a possible driver of demand for PLS over standard savings products (Kearney et al., 2010).

The final column of Table 3.3 shows regressions in which all three of these indices are included. The sign of the estimated coefficients is in the predicted direction for all three factors, but we only find statistical significance for the risk index and the financial constraint index. From these regressions, we estimate that increasing the risk index by one standard deviation is associated with an increase of R134,588 in MaMa deposits per branch, or an increase of 5.5% from the mean of R2.43 million. Meanwhile, a one standard deviation increase in the financial constraint index is associated with an increase of R 84,328 in total MaMa deposits, a 3.5% increase from the mean.

## TABLE 3.4
### UPTAKE OF MAMA AMONG BANK STAFF

This table presents estimates from OLS regressions run on the First National Bank staff dataset. In each regression, the dependent variable equals one if the employee has a positive balance in a particular saving product at any time during the sample period (Jan. 2005 - Mar. 2008). In Panel A we correlate demographic characteristics with the propensity to have either a standard 32-day savings account, a money market or standard 32-day account, or a MaMa account. *Ex-staff* indicate employees whose employment terminated at some point during the sample period. In Panel B we test whether previous banking behavior is correlated with the propensity to open a MaMa account, after controlling for all demographic characteristics contained in Panel A. *High* and *low savings before MaMa* are dummy variables indicating employees with above- and below-median savings, respectively, as a percent of income prior to opening a MaMa account. *High* and *low borrowing before MaMa* are defined similarly for net borrowers (and thus those with no accounts are the omitted group). All regressions contain 34 bank region fixed effects (regions are defined internally by First National Bank). Robust standard errors (reported in parentheses) are clustered at the region level. ***, **, * indicate significance at the 1%, 5%, and 10% level, respectively.

*Panel A: Demographic characteristics*

| *Dependent Variable:* | *Has 32-day Savings Account* | *Has 32-day or MM account* | *Has MaMa Account* |
|---|---|---|---|
| Age (<30 omitted): | | | |
| 30-39 | -0.074*** | -0.093*** | 0.056*** |
| | (0.005) | (0.005) | (0.011) |
| 40+ | -0.096*** | -0.104*** | 0.146*** |
| | (0.009) | (0.007) | (0.017) |
| Income decile (1st omitted): | | | |
| 2nd | 0.058*** | 0.095*** | 0.105*** |
| | (0.011) | (0.010) | (0.013) |
| 3rd | 0.087*** | 0.141*** | 0.153*** |
| | (0.013) | (0.013) | (0.016) |
| 4th | 0.106*** | 0.148*** | 0.190*** |
| | (0.015) | (0.011) | (0.010) |
| 5th | 0.107*** | 0.143*** | 0.203*** |
| | (0.015) | (0.014) | (0.012) |
| 6th | 0.082*** | 0.129*** | 0.182*** |
| | (0.009) | (0.011) | (0.013) |
| 7th | 0.083*** | 0.141*** | 0.178*** |
| | (0.018) | (0.015) | (0.012) |
| 8th | 0.058*** | 0.126*** | 0.174*** |
| | (0.010) | (0.012) | (0.012) |
| 9th | 0.046*** | 0.099*** | 0.168*** |
| | (0.016) | (0.017) | (0.014) |
| 10th | 0.018 | 0.064*** | 0.145*** |
| | (0.015) | (0.017) | (0.019) |
| Male | -0.061*** | -0.088*** | -0.042*** |
| | (0.004) | (0.005) | (0.005) |

**TABLE 3.4** – *continued*

| | | | |
|---|---|---|---|
| Race (mixed race omitted): | | | |
| Black | 0.093*** | 0.074*** | -0.044*** |
| | (0.011) | (0.014) | (0.011) |
| White | 0.003 | 0.022** | -0.042*** |
| | (0.007) | (0.009) | (0.009) |
| Asian | -0.012** | -0.004 | -0.044*** |
| | (0.006) | (0.009) | (0.006) |
| Ex-staff | -0.018** | -0.145*** | -0.104*** |
| | (0.007) | (0.019) | (0.009) |
| Region Fixed Effects | Y | Y | Y |
| Observations | 38,262 | 38,262 | 38,262 |
| *R*-squared | 0.036 | 0.055 | 0.046 |

*Panel B: Previous banking behavior*

| *Dependent Variable:* | *Opened a MaMa Account* | | |
|---|---|---|---|
| No saving or cheque acct. before opening MaMa | 0.046** | | |
| | (0.022) | | |
| Had saving account before opening MaMa | | -0.122*** | |
| | | (0.008) | |
| Had cheque account before opening MaMa | | -0.019 | |
| | | (0.021) | |
| High savings before MaMa | | | -0.012 |
| | | | (0.025) |
| Low savings before MaMa | | | -0.124*** |
| | | | (0.026) |
| Low borrowing before MaMa | | | -0.051*** |
| | | | (0.017) |
| High borrowing before MaMa | | | 0.054*** |
| | | | (0.019) |
| Demographic controls | Y | Y | Y |
| Region Fixed Effects | Y | Y | Y |
| Observations | 38,262 | 38,262 | 38,262 |
| *R*-squared | 0.048 | 0.058 | 0.060 |

*3.3.2. MaMa demand among bank employees*

While the FinScope survey data provides a representative sample of households near bank branches, the resulting averages are necessarily blunt measures of general geographic characteristics. In this section we use account-level data on employees of First National Bank employees to associate MaMa demand with individual characteristics. Table 3.4 presents results from linear probability models in which we estimate the relationship between income, age, gender, race, and past saving behavior with the propensity to open a MaMa account for 38,262 employees of the bank.[19] In all models we include 34 region fixed effects to account for geographic differences in MaMa uptake.[20]

Panel A of Table 3.4 compares demand for standard savings products and demand for MaMa across different demographic characteristics. The dependent variable in the first column is a dummy variable equal to one if the employee had a positive balance in a standard 32-day savings account at any time between January 2005 and March 2008, when the MaMa product was available. The second column is similar except it equals one if there was a positive balance in either a standard 32-day savings account or a special employee-only money market account that the bank made available in July 2007. The estimates in these first two columns can then be directly compared to the coefficient reported in the third column, in which the dependent variable equals one if the employee at any time had a positive balance in a MaMa account.

Given previous literature suggesting that PLS could be particularly attractive for low-income individuals, results on the relationship between income and the propensity to save in a MaMa account are of particular interest. In the regression results in Table 3.4, we estimate the relationship between income and MaMa uptake non-parametrically using income deciles. By comparing coefficient estimates across deciles, it is apparent that demand for both regular savings and PLS is hump-shaped in income, such that the lowest and highest deciles are least likely to have an account. This pattern can be more easily seen in

[19] Tables 3.4, 3.5, and 3.7 present linear probability models estimated by OLS, but essentially identical results are found if the models are estimated using probit or logit models.
[20] The data obtained from First National contained a region field that identified the region of South Africa in which the employee worked. We use these identifiers as fixed effects in the models in Tables 3.4, 3.5, and 3.7.

Figure 3.4, where we divide all employees of the bank by income decile, and plot the share of employees that had a standard savings product and the share that had a MaMa account at any point during the sample period for each decile. Although the results in Figure 3.4 are unconditional probabilities of having an account, they lead to the same conclusions as the coefficient estimates in Table 3.4. While the propensity to have an account is hump-shaped in income for both regular savings and PLS account, MaMa usage appears to be somewhat less sensitive to income than regular savings. Further, while the lowest-income employees were the least likely to use MaMa, a substantially higher portion had MaMa accounts (46%) than had standard savings products (31%). The share with MaMa accounts exceeds the share with regular savings across all income deciles.

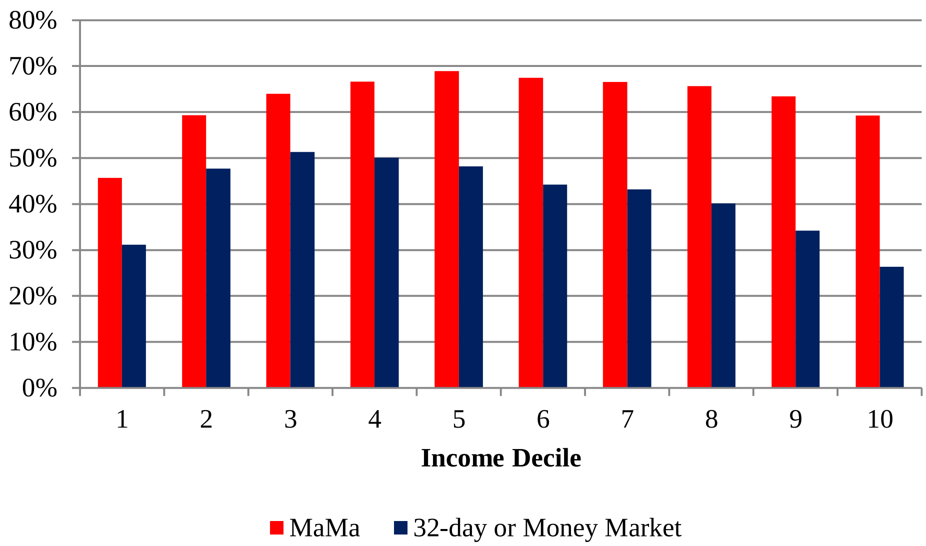



**FIGURE 3.4 - SHARE OF EMPLOYEES WITH STANDARD SAVINGS OR PLS ACCOUNTS, BY INCOME**
This figure plots the share of bank employees that have a standard savings account or MaMa account across ten income deciles. Employees are classified has having a standard savings account if they have either a regular 32-day notice account or a money market account. Income deciles divide the 38,262 employees into ten groups of 3,826 employees each based on estimated income.

When evaluating the relationship between income and demand for MaMa, it is important to keep in mind that the majority of bank employees earn substantially more than the median income in South Africa. Because of this, the 1st income decile of our sample includes salaries up to R60,000 per year, while the average household income in South Africa in 2006 was about R74,600 per year. However, even limiting to employees with the lowest salaries, the same patterns persist: 33% of those who make less than

R38,000 per year opened a MaMa account, while only 19% had a 32-day or money market account. Taken together with the findings in Section 3.3.1 above, it does appear that low income individuals are more likely to use a PLS account than a standard savings account, but demand for PLS follows a similar pattern across income groups.

One striking difference between usage of standard savings products and MaMa is that older employees are less likely to have a savings account but are more likely to open a MaMa account.[21] Relative to employees under the age of 30, employees in their 30s are about 9.3% less likely to have a 32-day savings or money market account, but 5.6% more likely to open a MaMa account. The differences are even larger for employees aged 40 and over. This runs contra to Figure 3.2, which shows that MaMa deposits came disproportionately from younger savers, and the findings in Table 3.3, in which we see that branches located in relatively younger areas had stronger MaMa demand. It is also in opposition to survey data collected in Tufano, Maynard, & Neve (2008) in which older respondents (in the U.S.) indicated substantially less interest in PLS products than younger individuals. However, it is consistent with Herring & Bledsoe (1994), who find that the aged are more likely to play the lottery. It is, of course, possible that these older individuals are putting their savings in an alternative account (perhaps to save for retirement) and that this is the reason why they are less likely to have a regular savings account, but this does not explain why they would be relatively more attracted to the PLS product. Another possibility is that older employees, who likely had a longer tenure at the bank, felt pressured to open MaMa accounts when the program was first starting.

With regards to gender, we find that males are 8.8% less likely to have a standard savings account but only 4.2% less likely to have a MaMa account. Thus, relative to standard savings, MaMa appears more attractive to men in particular, which is in line with Donkers, Melenberg, & Soest, (2001) who find that males are more risk tolerant than females. We also find substantial differences in MaMa demand across racial groups. While black employees are substantially more likely to have a savings account than

[21] 37.7% of bank employees are under 30, 36.3% are between 30 and 39, and 26% are over 40.

the other ethnicities, they are equally likely to have a MaMa account as whites and Asians. Meanwhile, individuals of mixed race are about 4.4% more likely to open a MaMa account than other racial groups.[22]

Panel B of Table 3.4 tests whether previous banking behavior is related to the propensity to open a MaMa account after controlling for demographic and geographic characteristics of employees. We find that employees who did not have any saving or cheque accounts at First National Bank were 4.6% more likely to open a MaMa account than those who already had active bank accounts. Assuming that most of these employees did not have active accounts at other banks, an assumption which seems reasonable given that these are employees of First National and therefore would be likely to bank there, this suggests that PLS-type products can indeed attract new savers who were previously sitting outside the formal banking sector.

The final two columns of Panel B delve further into this issue. In the middle column, we control separately for whether the employee actively used a savings or cheque account prior to opening a MaMa account, finding that in particular the use of a standard savings account significantly decreases the probability of opening a MaMa account, while employees who only had cheque accounts were equally likely as employees without any accounts to open a MaMa account. In the right-most column we separate employees by their net balances at the bank, defined as the sum of their cheque, 32-day, and money market accounts at the bank. Because employees were allowed to maintain negative balances in their cheque accounts, a significant portion (28%) are net borrowers from the bank, while 42% of employees have net positive balances, and the remaining 30% had no accounts at the bank. We split the group who are net savers into "high savers" and "low savers" depending on whether they had above- or below-median net savings at the bank as percentage of annual income. Similarly, we split the net borrowers into two groups, and thus end up with five groups of employees: above-median savers, below-median savers, those with no accounts, below-median borrowers, and above-median borrowers. Of these five groups,

[22] It is difficult to connect our results on race to previous literature due to cultural differences within race across countries. For example, Stinchfield & Winters (1998) find that Hispanic and African American youths have a higher propensity of gamble, but it is by no means clear that native Africans should be expected to have this same propensity.

employees who have borrowed the most from the bank are the most likely to open a MaMa account, followed by those with no accounts or above-median savings. Staff with small amounts of borrowing or small amounts of saving are the least likely to use MaMa. The differences between the groups are substantial; those with high net borrowing are nearly 18% more likely to open a MaMa account that those with a small amount of savings.

Taken together, our findings are indicative that demand for PLS comes from a broad range of consumers across all income levels, age brackets, and ethnicities. While these demographic characteristics are important predictors of PLS demand, the financial position and experience of an individual also affects the propensity to use a PLS account. In particular, demand for the MaMa product was strongest among financially constrained individuals, as evidenced both by the FinScope survey results as well as high demand by bank staff who had borrowed heavily from the bank. In addition, bank employees without any deposit accounts at First National exhibited strong demand for MaMa, suggesting that PLS can bring new savers into the banking system.

### 3.4. Banking behavior of PLS participants

#### *3.4.1. Did MaMa attract new savings?*

While the evidence in Section 3.3 suggests that MaMa attracted new *savers* into the banking system, it is also important to test whether PLS can generate significant new *savings*. Specifically, one worries that PLS might cannibalize regular savings rather than increasing total deposits. Because the MaMa program was not a randomized experiment, we cannot make explicitly causal inferences between usage of MaMa and increases in overall savings. However, we find no evidence that MaMa account holders reduced their savings in standard savings products.

Figure 3.5 provides a first look at the impact of MaMa on regular 32-day account balances. In this figure, we plot the average monthly growth rate of regular 32-day balances for two sets of bank branches: those that had above-median growth in MaMa account balances and those with below-median MaMa growth. Prior to the introduction of MaMa, average savings growth rates were very similar between the two sets of branches. After the MaMa program became active, those branches that had high average MaMa account growth also saw significantly higher growth in regular 32-day balances. If significant cannibalization of standard savings were occurring, one would expect just the opposite pattern.

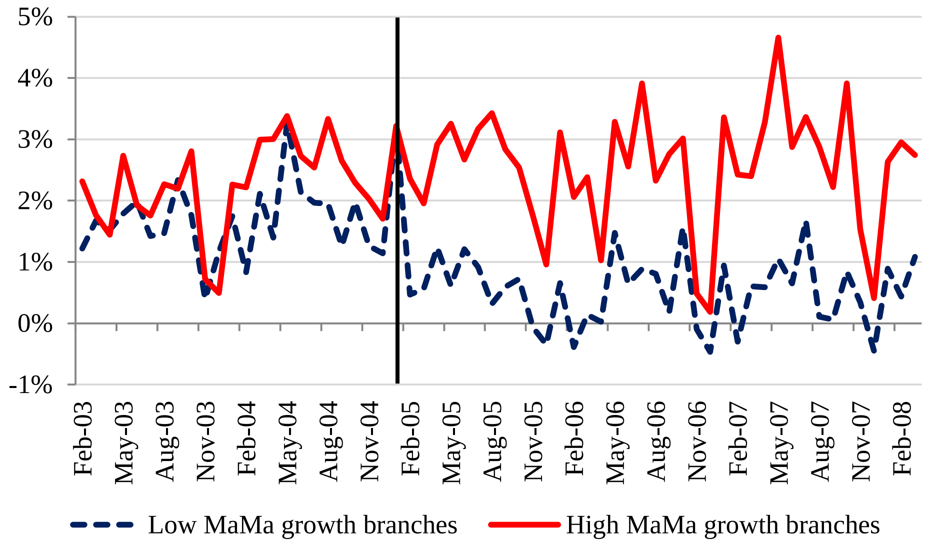



**FIGURE 3.5 - GROWTH RATES OF STANDARD 32-DAY SAVINGS**

This figure displays the average monthly growth rate of standard 32-day savings balances for two groups of First National's branches. Branches are divided based on their average monthly MaMa balance growth rate from Jan. 2005 – Mar. 2008. Those branches that had below-median MaMa growth are in the *low MaMa growth* group, while the remaining branches are placed in the *high MaMa growth* group. The figure shows average growth rates of standard 32-day balances both before and after the MaMa program, with the vertical line denoting the start of the program.

Account-level evidence from bank employees presents the same picture. In Table 3.5, we test whether employees who opened MaMa accounts also had higher net savings when the program ended in March 2008. We define net savings as the sum of all deposit accounts, including 32-day, money market, cheque, and MaMa, and then scale this amount by the annual income of the employee. After accounting for age, gender, race, income, and geographic fixed effects, we find that employees who opened MaMa accounts had on average higher net savings at the bank equal to about 1.1% of their annual income, a large difference when considering that the average net savings as a share of annual income is 3.5%. In the second column, we split the effect by whether the employee was a high saver, low saver, had no accounts, low borrower, or high borrower prior to opening MaMa, using the same definitions as in Table 3.4. For all five categories, employees who opened a MaMa account ended with higher net savings than those who did not open accounts. The largest effects were found for those who previously had no deposit

## TABLE 3.5
## MAMA USAGE AND OVERALL SAVINGS

This table presents OLS estimates of the relationship between opening a MaMa account and saving behavior at the end of the sample in March 2008, using data on First National Bank employees. *Opened a MaMa account* is a dummy variable equal to one if the employee had a MaMa account at any time during the sample period, regardless of whether the account was open in March 2008. *High savings, low savings, low borrowing,* and *high borrowing* are defined exactly as in Table 3.4, and interaction variables indicate how the effect of opening a MaMa account differed for each group. *Net savings* and *32-day balance* are winsorized at the 1% and 99% level to avoid outlier bias. The dependent variable in the final column is a dummy variable equal to one if the individual had a regular savings account (32-day or money market) or cheque account in March 2008. In this column, the sample is limited to bank employees that did not have these accounts in January 2005, when the MaMa program began. All regressions include the full set of demographic controls listed in Table 3.4, Panel A, as well as 34 geographic region fixed effects. Robust standard errors are clustered at the region level, and are reported in parentheses. ***, **, * indicate significance at the 1%, 5%, and 10% levels, respectively.

| *Dependent Variable:* | *Net savings in March 2008 (% income)* | | *32-day balance in March 2008 (% income)* | | *Has saving or cheque account in March 2008* Sample: Unbanked in Jan. '05 |
|---|---|---|---|---|---|
| Opened a MaMa account | 1.112*** | 2.113*** | 0.146*** | 0.320*** | 0.191*** |
| | (0.132) | (0.182) | (0.032) | (0.042) | (0.011) |
| High savings * opened MaMa | | -1.645*** | | -0.517*** | |
| | | (0.350) | | (0.045) | |
| Low savings * opened MaMa | | -1.864*** | | -0.137*** | |
| | | (0.141) | | (0.043) | |
| Low borrowing * opened MaMa | | -1.133*** | | -0.132*** | |
| | | (0.230) | | (0.038) | |
| High borrowing * opened MaMa | | 0.163 | | -0.182*** | |
| | | (0.291) | | (0.039) | |
| High savings before MaMa | | 7.267*** | | 1.280*** | |
| | | (0.239) | | (0.099) | |
| Low savings before MaMa | | 1.423*** | | 0.140*** | |
| | | (0.074) | | (0.030) | |
| Low borrowing before MaMa | | -1.023*** | | 0.024 | |
| | | (0.158) | | (0.025) | |
| High borrowing before MaMa | | -3.462*** | | -0.027 | |
| | | (0.181) | | (0.033) | |
| Demographic controls | Y | Y | Y | Y | Y |
| Region Fixed Effects | Y | Y | Y | Y | Y |
| Observations | 38,262 | 38,262 | 38,262 | 38,262 | 22,573 |
| *R*-squared | 0.020 | 0.105 | 0.008 | 0.050 | 0.214 |

accounts and employees with high levels of borrowing, who had higher net savings of 2.11% of income and 2.28% of income respectively. Meanwhile, employees who already had a small (large) amount of savings at the bank and opened a MaMa account increased net savings by 0.25% (0.47%) of income by March 2008.

Even more telling is the fact that individuals who opened MaMa accounts tended to have higher balances in their standard 32-day accounts in March 2008 as well. On average, employees who opened a MaMa account had higher 32-day balances equal to 0.15% of income in March 2008. Thus, employees who opened MaMa accounts tended to hold *more* in their standard savings accounts as well, suggesting that cannibalization of savings was not widespread.[23] Further, we find that this is true for nearly all groups of employees, whether they were borrowers or savers before opening a MaMa account. In particular, employees who opened a MaMa account and who previously had a low amount of savings or a small or large amount of borrowing held between 0.14% and 0.19% more of their annual income in 32-day savings, an increase of about 35% from the mean of 0.42% of income. The only group for which we find potential evidence of cannibalization are those employees who were above-median savers, who tended to hold 0.20% less in their 32-day accounts if they opened a MaMa account. However, as shown in column 2 of Table 3.5, even for this group overall savings was higher among those who opened a MaMa account.

The final column of Table 3.5 examines whether usage of MaMa lead to cross-over product usage at the bank. In this regression we limit the sample to employees that had no savings or cheque account in January 2005 (the first month of data, and the month in which the MaMa program was first offered), and test whether the employees in this sample who opened MaMa accounts were more likely to have a standard 32-days savings, money market, or cheque account in March 2008. We find that employees who

[23] However, given that the choice to open a MaMa account is endogenous, we cannot ascribe a causal relationship between opening a MaMa account and higher 32-day account balances. Indeed, it is quite possible that many of those who chose to open a MaMa account did so because of some external desire to save (e.g. a positive wealth or income shock) and thus increased their balances in standard savings accounts as well. If this is the case, we might observe that these individuals have higher 32-day savings balances than those who did not open MaMa accounts, but they may have had even higher 32-day balances had MaMa not be available.

opened a MaMa account were 19% more likely to have another deposit account at First National than employees who did not open an account. This suggests that, at least in the case of First National Bank, previously unbanked individuals who use a PLS product are also more likely to open a standard account along with the PLS account.

*3.4.2.MaMa demand and lottery gambling*

If MaMa did not divert funds from standard savings, where did the additional balances come from? Kearney et al. (2010) hypothesize that "the introduction of prize-linked savings products could provide an alternative to lottery tickets that offers a higher (and certainly less negative) return on one's 'investment.'" Given the similar payoff structure, and previously documented substitutions between gambling and saving (Consumer Federation of America & The Financial Planning Association, 2006; Lusardi et al., 2011), PLS could act as a natural substitute for lottery gambling. Indeed, experimental evidence in Atalay et al. (2012) shows that the introduction of a PLS program can reduce lottery expenditure.

The fact that the MaMa program was shut down by a lawsuit pursued by the National Lottery of South Africa is indirect evidence that MaMa did indeed reduce demand for lottery gambling. We use random variation in the size of the jackpot of the National Lottery to more directly test whether PLS demand and lottery demand are linked. Lottery prize winners in South Africa are drawn each Wednesday and Saturday, and the size of the jackpot is a function of the number of lottery tickets sold in each period. However, when a grand prize winner is not drawn, the jackpot rolls over to the next period, creating random periods in which jackpots are substantially larger than others. If MaMa is a substitute for lottery gambling, one would expect that MaMa demand should be low in periods when the lottery jackpot is particularly high. We use daily data on both the amount of new deposits placed in MaMa accounts and the number of new MaMa accounts created to calculate the total amount of new balances and number of new accounts at the bank during each draw period. We can then use a time series regression to test whether MaMa demand (i.e. the number of new accounts created or amount of new funds deposited) was lower during draw periods with larger lottery jackpots.

Table 3.6 presents results from this estimation. The main independent variables in these regressions are dummies for the estimated size of the jackpot for each particular draw. These estimates were published by the National Lottery at the beginning of each draw period to generate demand for the lottery, and were hence readily available for potential consumers.[24] We include both the contemporaneous jackpot as well as the jackpot from the previous draw to account for possible lags in the relationship between lottery jackpots and MaMa demand.[25] We include a number of controls to account for other factors that may affect MaMa demand, including an indicator of whether the draw took place on a Saturday or a Wednesday and also an indicator of draw periods which were shorter due to bank holidays. Further, we include broad time dummies which split the sample into three time periods: January – December 2005, January 2006 – March 2007, and October 2007- March 2008. Between March and October 2007 the National Lottery was shut down due to disputes over the ownership of the license to run the lottery, and so there are no jackpot draws for this time period (and these months are not included in the regressions). Including these time dummies helps take account of long-run trends in the growth of MaMa accounts. We also control for the growth in regular 32-day savings balances and accounts at the bank, to account for factors that might be driving savings in general at the bank. Lastly, we include a lag of the dependent variable to help remove serial correlation, as well as a time trend for the new funds deposited regression, which shows a noticeable trend. Newey-West standard errors which account for up to 2 weeks of remaining serial correlation are reported.

In support of the hypothesis that PLS can act as a substitute for lottery gambling, we show that MaMa demand was lower in draw periods with larger jackpots. When the anticipated jackpot was between R4 million and R7 million (the third quartile) or over R7 million (fourth quartile), there was a reduction in total new deposits in MaMa accounts of 11.9% and 14.6%, respectively. Similarly, when

[24] Actual jackpots are very close to estimates. Estimated jackpots are derived from estimates of lottery ticket sales, combined with any jackpot which was rolled over from previous periods, or any special promotions (such as a guaranteed jackpot).

[25] For example, it possible that excitement from a large jackpot in the previous draw could continue to diminish demand for PLS.

## TABLE 3.6

### MAMA GROWTH AND THE NATIONAL LOTTERY

This table relates overall MaMa demand to the size of the jackpot available in the South Africa National Lottery. Each week, winning lotto numbers are drawn on Wednesday and Saturday. For each regression, the dependent variable is an indicator of growth in MaMa usage over the 3-day period (M-W or Th-S) preceding the draw. *ln(New funds deposited)* is the log of total Rand deposited in new accounts during the draw period , and *# of new accts. opened* is the total number of new MaMa accounts opened over the draw period Jackpot sizes were estimated and published by the National Lottery prior to the draw. We non-parametrically divide jackpots into 4 quartiles, where the largest jackpots are typically due to rollovers or guaranteed prizes. Both the contemporaneous jackpot as well as the lagged jackpot are included in the model. *Saturday* indicates draws that were done on Saturday, and controls for time-of-week fixed effects. *2005 dummy* and *post-shutdown* are time fixed effects that control for the initial year of the program (2005) and the period after the lottery re-opened (Oct. 2007-Mar. 2008). *Few business days* controls for draw periods that covered less than 3 business days due to holidays. *Savings growth* controls for the growth in regular 32-day deposit balances ($1^{st}$ column) and accounts ($2^{nd}$ column) at First National during the draw period. To remove serial correlation, we include lagged values of the dependent variable, as well as a time trend for the amount of new funds deposited, which shows a noticeable trend. Newey-West standard errors that account for up to 2 weeks of remaining serial correlation are reported. ***, **, * indicate significance at the 1%, 5%, and 10% levels, respectively.

| *Dependent Variable:* | *ln(New funds deposited)* | *# of new accts. opened* |
|---|---|---|
| Estimated Jackpot size (< R3 million omitted): | | |
| R3 million - R4 million | -0.0311 | -137.0 |
| | (0.0584) | (144.5) |
| R4 million - R7 million | -0.119*** | -389.1*** |
| | (0.0416) | (116.5) |
| > R7 million | -0.146*** | -288.7** |
| | (0.0495) | (138.4) |
| Last period jackpot: | | |
| R3 million - R4 million | -0.145*** | -275.5* |
| | (0.0496) | (149.4) |
| R4 million - R7 million | -0.121*** | -324.8** |
| | (0.0398) | (136.9) |
| > R7 million | -0.0591 | -252.1* |
| | (0.0491) | (140.1) |
| Saturday | -0.0479 | 45.76 |
| | (0.0387) | (87.72) |
| 2005 dummy | -0.764*** | -854.5*** |
| | (0.117) | (150.2) |
| Post-shutdown (Oct. 2007-Mar. 2008) | -0.155* | -1,069*** |
| | (0.0827) | (180.6) |
| Few Business days | -0.436*** | -1,240*** |
| | (0.0721) | (160.4) |
| Savings Growth (%) | -3.431 | 16,370*** |
| | (3.439) | (5,072) |
| Lagged dependent variable | 0.394*** | 0.620*** |
| | (0.0656) | (0.0575) |
| Time trend | -0.00745*** | |
| | (0.00111) | |
| Observations | 276 | 276 |

jackpots are in the third (fourth) quartile total new MaMa accounts created decreased by about 389 (289), a decrease of 11.2% (8.3%) from the mean of 3,483 new accounts created per draw period.[26] Further, we also find evidence that one-period (3 days) lagged large jackpots also have a negative impact on MaMa demand relative to small jackpots, suggesting that even the recent memory of a large prize may entice some would-be PLS savers to purchase lottery tickets.[27]

These results strongly suggest that MaMa was indeed acting as a substitute for lottery gambling, meaning that reduced lottery expenditure is likely one of the main sources for additional savings deposited in PLS accounts. However, this evidence must be weighed against the fact that we find no noticeable increase in MaMa demand when the National Lottery was shut down in March 2007 nor is there a decrease in demand when it re-opened in October of 2007. While these are only two data points and there are other possible factors that could be affecting MaMa uptake during this period, it is surprising that there was not a discontinuous or even noticeable increase in MaMa usage during this period. Future research that directly connects PLS usage with lottery expenditure is needed to fully resolve this question.

### 3.5. Prize winning and saving

#### *3.5.1. Prize winner's own behavior*

The very aspect that makes prize-linked savings unique—randomly assigned prizes—also makes it an interesting environment to study what individuals will do with a cash windfall. First National Bank held monthly drawings in which each account holder was given one entry into the drawing for each R100 held in her account. Each month, a grand prize of R1 million was awarded, along with two prizes of

[26] It is somewhat odd that the relationship between new MaMa accounts created and jackpot size is non-monotonic, as the estimated impact of jackpots in the 3rd quartile is larger than that of the 4th quartile. However, standard errors are large enough that we cannot statistically rule out that the true coefficient for the 4th quartile is indeed larger than that of the 3rd quartile, leaving open the possibility that this anomaly is simply due to statistical noise.
[27] We find no evidence of a relationship for lags longer than 1 draw period (3 days).

R100,000, ten prizes of R20,000, and one hundred prizes of R1,000.[28] The random drawing was performed by a third party company, and Figure 3.3 shows that the actual number of prizes awarded at each branch lines up very closely with the number of expected prizes, alleviating concerns that the drawing was not truly random. First National provided us with the monthly time series of MaMa account balances (but not other saving or cheque account balances) for each prize winner from January 2005 through June 2008. In addition, we have data on the demographic characteristics of prize winners, as well as the total amount of deposits at First National in other accounts in the month of the win.

Because prizes were awarded randomly, conditional on the MaMa account balance prior to the win, we can view this as an exogenous shock that affects the financial situation of an account holder, and test whether that individual continues to invest in PLS and, if so, how much he holds in his account. Ex ante, it is unclear whether winning a prize will increase or decrease an individual's demand for PLS. On one hand, if an individual has invested in PLS with the hopes of dramatically improving his socioeconomic status, once a large prize has been won he might be expected to close his account and invest in more standard investment products, since his goal has been achieved. This effect should be especially prevalent for larger prizes. On the other hand, it is also possible that lottery play has an addictive aspect to it (Guryan & Kearney, 2010), and that winning a prize serves to strengthen this tie.

In Table 3.7 we estimate the probability that a prize-winner still has a MaMa account open six months or one year after winning, relative to employees of the bank who did not win prizes. Using bank employees as a control group is not ideal, as they are not necessarily directly comparable to prize winners who were not employees[29], but this is the only account-level data available to us which contains individuals that did not win prizes. To estimate these regressions, for each month we include all bank employees who had an open account in that month as well as all prize winners in that month, and then test whether prize winners had a higher propensity to have an open account six months or one year after that

[28] As discussed in Section 3.2, in September 2007 the bank doubled the number of prizes assigned (such that four R 100,000 prizes were awarded, twenty R20,000 prizes, etc.), except for the grand prize.
[29] There were only 59 employees who also won prizes, out of a total of 4,965 total prizes awarded, so we lack sufficient sample size to limit to only employee winners.

point in time. This means that many employees are included in the sample multiple times. For example, if an employee has a MaMa account in March 2005, we check whether he still has his account active in September 2005 (6 months later) and in February 2006 (12 months later), and compare this to prize winners who won prizes in March 2005. If the same employee also has his MaMa account open in April 2005, he will be included again in the sample, except now we check if his account remains open in October 2005 and March 2006. Because individuals are repeated in the sample, we cluster standard errors at the individual level to account for correlation between repeated observations. It is vital in these regressions to include year-month fixed effects so that we are comparing employees and prize winners in the same months to each other. In addition, it is critical to control for the MaMa balance prior to winning, since winning a prize is only random conditional on the amount held in the account. We control for the MaMa balance prior to winning non-parametrically by including dummies for each decile of the distribution. In addition to these controls, we also include all demographic characteristics as in Table 3.4 in the regression, as well as controls for whether the individual had other accounts at First National Bank, the natural log of the total balance held in those accounts, and the number of months the individual had a MaMa account prior to winning a prize.

The main variable of interest in these regressions are dummies indicating the prize won by an account holder. We split prize amounts into four categories: R1,000 to R19,999, R20,000 to R99,999, R100,000 to R 999,999, and R1,000,000. We use these ranges because a few prize winners won multiple prizes in a given month, and hence there are a few cases in which the prize amount is not exactly R1,000, R20,000, R100,000, or R1 million. However, the vast majority of winners in each category won only a single prize, and hence are exactly at the lower bound of that category.

We find that R1,000 prize winners are less likely to keep their MaMa accounts open than bank employees both six months and one year after winning. Coefficients for R20,000 and R100,000 prize winners are also negative at both horizons, although statistical significance for these groups is only found

## TABLE 3.7
### THE EFFECT OF PRIZE WINNING ON MAMA DEMAND

This table presents OLS regressions which test the effect of winning on MaMa account holders, as compared to bank staff. Data is at the individual-month level. In each regression, we control non-parametrically for the decile of MaMa balances 1 month prior to winning, as well as all demographic controls contained in Table 3.4, thus focusing only on the random event of winning a prize. The first two columns test whether winning a prize affects one's propensity to continue to use a MaMa account 6 months or a year after winning. While each winner is only included in the sample once, each month of observation for bank staff is included in the sample if that individual had a MaMa account 6 months or 12 months prior to that month. The second two columns test whether winners who keep their MaMa accounts open after winning have higher or lower balances in those accounts than bank employees who did not win. Individuals are included in the sample if they had an active account 6 or 12 months ago and have an active account at the snapshot. All regressions include year-month fixed effects. MaMa account balances used as dependent variables in the last two columns are winsorized at the 95$^{th}$ percentile to avoid outlier bias. Robust standard errors are in parentheses, and are clustered at the individual level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

| *Dependent Variable:* | *Has MaMa Indicator* | | *MaMa Acct. Balance* | |
|---|---|---|---|---|
| Sample: | Had MaMa account when prize was won | | Had MaMa account when prize was won & at snapshot | |
| Snapshot - No. months after win: | 6 | 12 | 6 | 12 |
| Prize Category | | | | |
| R1,000 to R19,999 | -0.017** | -0.042*** | 6,295.784*** | 4,713.324* |
| | (0.008) | (0.013) | (2,159.515) | (2,857.951) |
| R20,000 to R99,999 | -0.021 | -0.008 | 31,911.117*** | 24,218.909*** |
| | (0.016) | (0.022) | (5,280.390) | (5,873.326) |
| R100,000 to R999,999 | -0.037 | -0.137** | 29,753.159*** | 29,715.588*** |
| | (0.038) | (0.065) | (6,294.463) | (8,639.597) |
| R1,000,000 | 0.054*** | 0.041 | 95,433.053** | 16,588.566* |
| | (0.014) | (0.042) | (44,997.952) | (9,535.495) |
| | | | | |
| Prior MaMa balance decile fixed effect | Y | Y | Y | Y |
| Demographic controls | Y | Y | Y | Y |
| Year-Month Fixed Effect | Y | Y | Y | Y |
| | | | | |
| Observations | 439,152 | 323,714 | 380,363 | 257,956 |
| *R*-squared | 0.152 | 0.150 | 0.356 | 0.228 |

for R100,000 prize winners at the 12-month horizon.[30] However, the economic magnitudes of these estimates are not overly large. We estimate that winners of the R1,000 prize are 4.2% less likely keep their account open one year after winning, a small reduction from the mean of 79.7%. Even for R100,000

[30] Because there are substantially more R1,000 prize winners, estimates of these coefficients tend to be much more precise than estimates for other prize categories.

prize winners, which are 13.7% less likely than non-winners to keep their account open for a year, the likelihood of keeping their account open remains well above 60%. Meanwhile, we also find that winners of the grand prize are somewhat more likely to keep their account open six months and one year after winning (although the one-year coefficient is not statistically significant). The fact that the finding reverses for the largest prize winners suggests that winning the jackpot could have some addictive aspect, or perhaps individuals feel that they have enough money that they can afford to gamble a bit. Regardless, the estimated coefficients are again not large: R1 million prize winners are only 5.4% more likely to keep their account open for six months, and 4.1% more likely for a full year.

In the last two columns of Table 3.7, we test whether prize winners keep more in their MaMa accounts after winning, conditional on keeping their account open. These regressions are very similar to those in the first two columns, except that here the sample is limited to prize winners and staff who have active MaMa accounts both when the prize was awarded and at the snapshot (e.g. 6 or 12 months later). The dependent variable is the MaMa account balance at the 6- or 12-month horizon, a figure which we winsorize at the 95$^{th}$ percentile to avoid undue influence of outliers.[31] It should be noted that when prizes were awarded the amounts were automatically deposited into the winner's MaMa account, so there is an immediate increase in a winner's MaMa balance in the month following the win. Thus, we are testing whether prize winners leave these amounts in their accounts or even increase their investment, or whether they take their winnings out of the accounts for other uses.

Across all levels of winnings, prize holders keep substantially more in their accounts than non-winners, even a full year after the prize was awarded. Given that each prize-holder experienced a wealth shock, this is perhaps unsurprising. What is more surprising, however, is the estimated size of the effect. In particular, individuals who won R1,000 hold R6,296 and R4,713 more in their accounts than non-winners six and twelve months after winning, respectively. These results are conditional on the amount held in the account the month before winning, and thus suggest that small prize winners who keep their

[31] We also obtain similar results if we use ln(MaMa Balance) as the dependent variable.

account open on average increase their investment in PLS by substantially more than the value of the prize itself. A similar pattern holds for winners of R20,000, who hold R31,911 more in their accounts six months after winning, and R24,219 one year after winning. These are very large effects, given that the median account holder maintains a balance of about R400, while the average account holds R17,800.

Large prize winners also maintain significantly higher account balances. We estimate that winners of R100,000 keep nearly R30,000 more in their MaMa accounts on average a full year after winning. Winners of R1 million have just under R100,000 more in their accounts six months after winning, but this amount drops to R16,589 a year after their win.

For most account holders, winning a cash prize leads to increased investment in MaMa. In the case of smaller prizes, we find that the average increase in deposits actually exceeds the amount of the prize, suggesting that the increased investment is more than a pure wealth effect. Rather, this evidence is consistent with the idea that winning a prize may add to the excitement of PLS and hence lead to increased demand.

3.5.2. *Effect of prize on other's behavior*

Large prizes can also have an impact on the behavior of others. In this section we test whether prize winners create a "buzz" at a particular bank branch, leading to increased demand for PLS at that branch relative to other bank branches. To do this, we follow the methodology of Guryan & Kearney (2008), who find that in the week following the sale of a winning lottery ticket, lottery ticket sales at the winning store increase substantially relative to other sales locations. Similarly, we test whether bank branches where the jackpot winner holds an account experience excess demand for MaMa in the month following the win. To do so, we estimate the following specification:

$$MaMaGrowth_{bt} = \alpha_k + \gamma_k w_{b(t-k)} + \delta_k \ln(MaMaBal_{b(t-k)}) + \mu_{k,t} + \varepsilon_{k,bt}$$

where $b$ indexes bank branches, $t$ indexes months, $k$ indexes months since the drawing, $MaMaGrowth$ is the monthly log growth rate of MaMa balances at the branch, $w$ is a dummy variable equal to one if the jackpot winner's account was at branch $b$, $\ln(MaMaBal)$ is the natural log of total MaMa deposits held at the branch, and $\mu$ is a fixed month effect. With this setup, $\gamma_k$ is the estimated effect of having a R1 million winner at the branch $k$ months after the drawing relative to all other branches. This specification is estimated once for each value of $k$. It is crucial in these specifications to condition on the amount of MaMa deposits held at the branch, as each branch only has the same chance of having a jackpot winner conditional on the amount of MaMa deposits held at the branch that month. In addition, when calculating the growth rate of MaMa balances we remove the jackpot winner's account from the total balance since the winner receives R1 million in her account in the month following the win, which has a drastic impact on growth rates.

Panel A of Figure 3.6 plots estimates of $\gamma_k$ for values of $k$ ranging from 3 months prior to the drawing to 3 months after, as well as 95% confidence intervals for the estimate. As expected, coefficient estimates are statistically indistinguishable from zero for all months prior to the drawing, which verifies the identifying assumption that the assignment of the prize was truly random conditional on MaMa deposits held at the branch. In the month following the drawing we find that MaMa deposits grow by an excess of 11.6% at the branch which had the winning MaMa account. Note that this is a monthly growth rate. Across the whole sample, the average monthly growth rate of MaMa balances was 13.3%, and so having a jackpot-winning account holder increases the growth rate of deposits by 87%. However, the effect does not persist past one month. In the following month, growth at the winning branch is again indistinguishable from that of other branches. At the same time, the growth rate does not shrink below that of non-winning branches, such that this one-time shock results in a permanent *level* change in the amount of MaMa deposits at the branch.[32]

In Panel B of Figure 3.6 we plot a similar picture except in this case the dependent variable in the regression is the change in the number of MaMa accounts in month $t$. The estimated effect one month after the prize is not quite statistically significant (p-value=0.07), but the point estimate is similarly large.

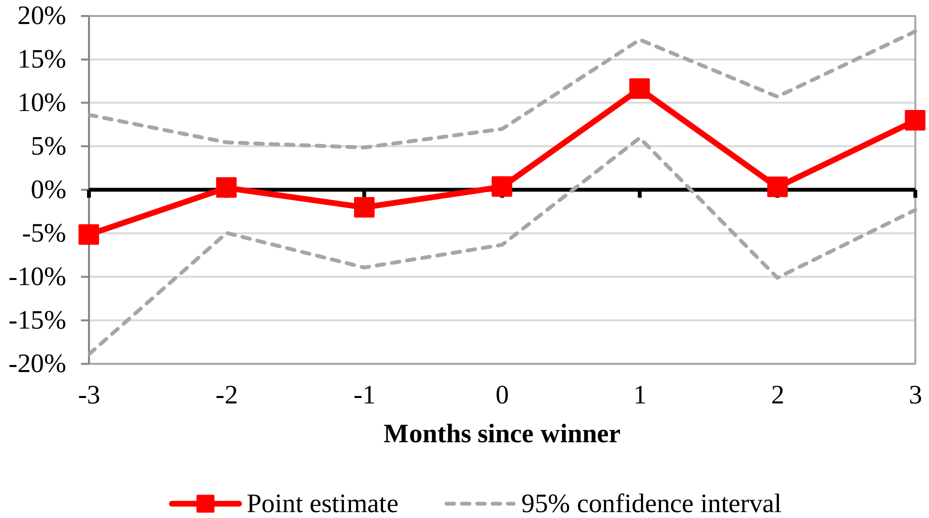
[32] In unreported results, we also find that branches with a higher than expected number of prizes experience abnormally high growth in MaMa balances in the following month. In addition, our results also hold if we change $w$ to be a dummy equal to 1 if any large prize (i.e. greater than R1,000) was won by an account holder at a particular branch, although the estimated impact is smaller at 2.9% excess growth in MaMa balances.

**FIGURE 3.6 - EFFECT OF JACKPOT PRIZE WINNER ON LOCAL MAMA DEMAND**

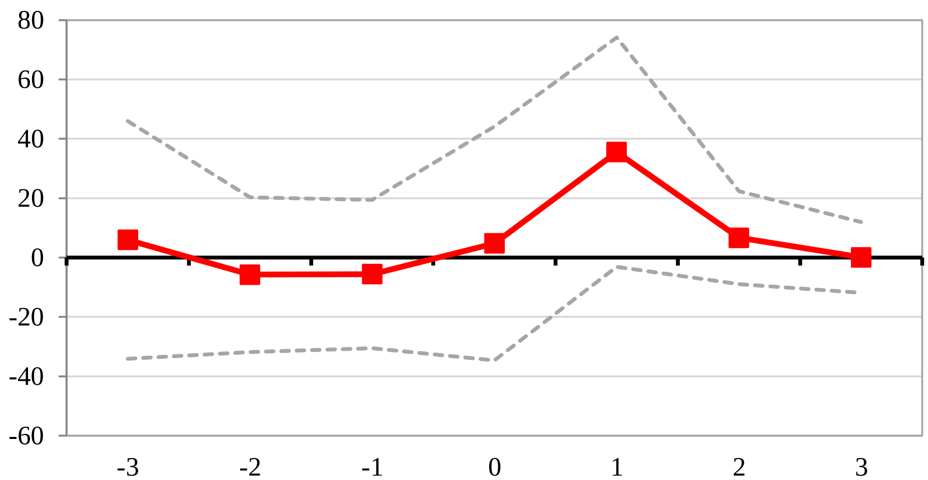
This figure shows the impact of having a million-Rand prize winner on local MaMa demand. Each panel displays coefficient point estimates and 95% confidence bands from seven separate regressions which test the lead and lag effect of a jackpot win. Panel A shows the effect of having a million-Rand winner on the excess monthly growth rate of MaMa balances at the same branch, relative to all other bank branches. Panel B is similar, except it shows the impact of a jackpot win on the change in the number of MaMa accounts at the branch. Panel C displays the spillover effect of a jackpot win on the growth rate of MaMa balances at branches that are within 10km of the winning branch. Regressions are estimated by OLS, and exact specifications are described in detail in the text. Confidence intervals are based on robust standard errors which are clustered at the branch level.

**FIGURE 3.6 -** *continued*

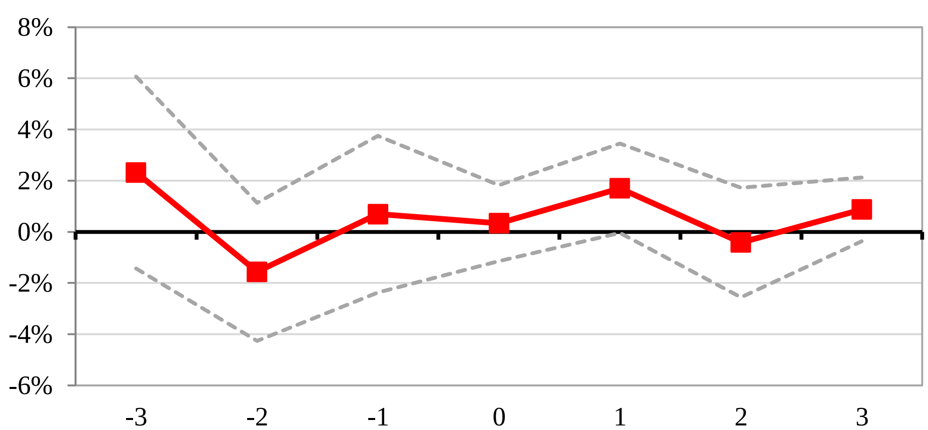
*Panel A: Excess growth of total MaMa deposits at winning branch*




*Panel B: Change in number of MaMa accounts at winning branch*




*Panel C: Excess growth of total MaMa deposits at nearby branches*



Specifically, having a jackpot winner increases the number of new MaMa accounts at the winning branch by about 36 accounts, a 70.5% increase from the mean increase of 51 new accounts.

Finally, we also test whether there is a spillover effect to other nearby First National branches. Here, we alter the definition of $w$ such that it is a dummy equal to 1 if a branch within 10km (6.2 miles) has an account holder that wins the jackpot. In these regressions we drop the winning branches from the sample, so as to focus entirely on estimating the spillover effect by itself. Results are presented in Figure 3.6, Panel C. We find weak evidence that branches experience excess MaMa deposit growth of about 1.7% in the month after a nearby branch has a jackpot-winning account. This result is just outside of the range of statistical significance (p-value=0.056), which is perhaps unsurprising given that effect is an order of magnitude smaller.

Our results are consistent with the findings in Guryan & Kearney (2008), who also find strong same-store effects for selling a winning lottery ticket and much smaller spillover effects to other nearby stores. In the context of prize-linked savings, our results show that prize-winning can indeed create a "buzz" that results in significant and permanent increases to savings held in the PLS product even by those who did not win a prize. In this way, the prizes themselves can act as a self-contained mechanism to generate savings.

### 3.6. Conclusions

The raw growth of the MaMa program confirms that, in South Africa at least, there was strong "unmet consumer demand…for saving products that offer the (remote) prospect of changing current wealth status, rather than incrementally building wealth with certainty" (Kearney et al., 2010). By relating personal characteristics to PLS usage, we find that demand for MaMa came in particular from financially constrained individuals—consumers who had relatively high amounts of debt or who reported having to go without necessities because of a lack of funds. In addition, we find evidence that higher risk tolerance and lower levels of optimism are also positively related to PLS demand. These results are in line with the idea that the attraction of "winning big" is strongest for individuals who have the greatest desire to obtain a life-changing amount of money, such as low-wealth or depressed individuals. Further, we did not find a relationship between financial knowledge and PLS uptake, suggesting that the relatively low observed levels of precautionary savings and high amounts spent on lottery gambling are not due to a lack of financial sophistication such as misunderstanding compound interest.

Building on this, our evidence suggests that prize-linked savings act more as a substitute for lottery gambling rather than standard savings. In particular, we do not see any evidence that the MaMa program cannibalized savings, and instead find the reverse: branches with higher MaMa usage also saw expansion of regular savings, and individuals who opened MaMa accounts typically increased their balances in standard savings accounts (although these relationships are not necessarily causal). Meanwhile, demand for MaMa was highest when the jackpot of the National Lottery was lowest, suggesting that the two were acting as substitutes. Because principal is preserved in PLS, it offers a huge advantage over lottery gambling and thus it is not surprising that it draws funds from lottery play.

Finally, we also show that prize-winning has a dramatic effect on the saving behavior of both the winner as well as those nearby. Prize winners are slightly less likely to keep their accounts open, but conditional on keeping the PLS account open tend to increase balances held in PLS by substantial amounts, in some cases by even more than the amount of the prize won. Further, large prizes create a local "buzz," leading to dramatically increased demand for PLS at the winning branch in the month following the win.

These findings are important for academic researchers seeking to understand saving and gambling behavior, as well as policy makers who are considering alternative policies geared toward increasing savings. Prize-based incentives such as those offered in PLS products can successfully attract new savers and new savings, and would also likely decrease the amount of lottery gambling. Our evidence shows that there is a potentially large group of consumers who have little or no savings because they value the chance, however remote, of winning a life-altering prize.

# APPENDICES

# A

# Appendix to Chapter 1

## A.1. Dismissal from court

In the text, I argue that dismissal from court is equivalent to liquidation for most firms. To verify this, I randomly selected 100 dismissed firms that filed for Chapter 11 and examined the reasons for their dismissal using court documents on the U.S. Court's Public Access to Court Electronic Records (PACER) system. In general, the reasons for dismissal can be sorted into four categories: (1) the debtor failed to follow court procedure, such as failure to file specific documents, failure to hire counsel, or failure to show up in court; (2) the debtor is deemed to have abused the system by filing in bad faith, or filing repeatedly without making efforts to repay its debts; (3) there is no possibility that the debtor can successfully reorganize; (4) the debtor has reached a settlement with its creditors and therefore no longer needs bankruptcy protection. Unsurprisingly, the reason for dismissal varies considerably depending on which party files the motion. When the trustee or court files the motion for dismissal, it is typically because the debtor did not obey a court order of some sort, but in a significant minority of cases it is also because there is no hope of reorganization. When a creditor files a successful motion the reason for dismissal is often because the debtor has abused the bankruptcy system in some way. Debtor-filed motions, however, are nearly equally split between debtors who have no hope of reorganizing, and who wish to leave bankruptcy and simply liquidate without incurring further legal fees, and debtors who have either found a buyer or have reached a settlement with their creditors. It should be noted that in many cases when a debtor sees no hope of reorganization and files for dismissal of the case the court has previously granted motions in favor of the creditors, such as lifting the automatic stay or denying the use of cash collateral. Thus, although these cases appear to be voluntary shutdowns, the debtor really had no other choice available due to previous actions of the court (Morrison, 2005).

Overall, dismissal is a close equivalent to conversion in many cases; the firm is dismissed from court but will still be liquidated.[1] Based on information in PACER, 53 of the dismissed firms I examined expected to liquidate shortly after dismissal. An additional 33 firms were dismissed from court without resolving their financial distress and were likely liquidated as well, although the PACER documents did not make that explicit. Only 10 firms were dismissed because they had reached a settlement with their creditors. Of the remaining 4 firms, 3 were sold as going concerns and one was dismissed because it wasn't actually in financial distress. By and large, dismissal from Chapter 11 is akin to conversion to Chapter 7.

In the text, I show that firms that are dismissed from busy bankruptcy courts are substantially more likely to re-file for bankruptcy. In particular, the increased recidivism is driven by dismissed firms that re-file for Chapter 11 (as opposed to Chapter 7) bankruptcy. Of the 100 dismissed firms discussed above, 10 re-filed for Chapter 11 bankruptcy within 3 years of their initial filing, while 6 re-filed for Chapter 7. Nearly all (8 out of 10) of the "Chapter 22" filings were by firms that were dismissed from court without resolving their financial distress but for whom court documents do not explicitly show that the debtor planned to liquidate out of court. Meanwhile, 4 out of 6 of the firms that re-entered court in Chapter 7 were firms for whom liquidation was expected after dismissal. Assuming that this random sample of 100 firms is representative of the broader set of firms, this would suggest that most "Chapter

[1] Indeed, many motions for dismissal are joint motions for either dismissal or conversion to Chapter 7.

22" re-filers are firms that, after dismissal, attempt to continue operations and possibly renegotiate outside of court, but failing to do so are forced to re-enter bankruptcy.

## A.2. Data construction

*A.2.1 LexisNexis' data coverage*

As stated in the text, LexisNexis has essentially complete coverage of bankruptcy filings in their dataset. This can be verified by examining the aggregate filing statistics available from the U.S. Courts system.[2] Specifically, LexisNexis contains a total of 21,833 business Chapter 11 bankruptcy filings in the 50 states and the District of Columbia between 2004 and 2007. During the same period, U.S. Courts report that a total of 25,095 business Chapter 11 filings. The discrepancy between the two datasets can be fully accounted for by differences in how a "business" bankruptcy filing is defined. The U.S. Courts count a filing as a business filing if the majority of the debt associated with the filing is business-related, and thus some of the "business" Chapter 11 filings will include individuals who file for Chapter 11 with business debt. Meanwhile, LexisNexis only counts a filing as a business filing if the debtor declared himself a corporation or partnership on the voluntary petition for bankruptcy. To ensure that LexisNexis' data contains complete coverage, I randomly selected two dates and compared the total number (both business and non-business) of Chapter 11 filings in LexisNexis to the U.S. Courts statistics for a random subset of 14 bankruptcy districts. For these groups, LexisNexis had information on 693 Chapter 11 filings as compared to 700 recorded by the U.S. Courts system. Hence, LexisNexis has about a 99% coverage rate, indicating that the discrepancy in business Chapter 11 filings is due entirely to how a "business" is defined by the two sources.

While there were a total of 21,833 business Chapter 11 filings during the sample period, many of these filings are made by related entities. Often, when a company files a Chapter 11 petition, each of its subsidiaries will file separate petitions in the same court on the same day, or soon thereafter. Because these cases are typically consolidated and managed jointly, for my purposes they should be treated as a single case. I identify related filings by comparing the company name, address, filing date, and exit date

[2] Available at http://www.uscourts.gov/Statistics/BankruptcyStatistics.aspx.

## TABLE A.1
## INDUSTRY DISTRIBUTION

This table presents the 30 Fama-French industries and the number of sample firms in each industry. Definitions of the industries are pulled from Kenneth French's website at http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html. Where possible, I use the SIC code reported by Capital IQ to classify the firms. In cases where the SIC code is not provided, I use the description of the industry from The Deal Pipeline to classify the firm.

| Fama-French industry code (30 industries) | No. of firms | % |
|---|---|---|
| Food Products | 92 | 2.77% |
| Beer & Liquor | 4 | 0.12% |
| Tobacco Products | 3 | 0.09% |
| Recreation | 144 | 4.33% |
| Printing and Publishing | 49 | 1.47% |
| Consumer Goods | 60 | 1.80% |
| Apparel | 26 | 0.78% |
| Healthcare, Medical Equipment, Pharmaceutical Products | 204 | 6.13% |
| Chemicals | 13 | 0.39% |
| Textiles | 18 | 0.54% |
| Construction and Construction Materials | 383 | 11.51% |
| Steel Works Etc | 20 | 0.60% |
| Fabricated Products and Machinery | 148 | 4.45% |
| Electrical Equipment | 12 | 0.36% |
| Automobiles and Trucks | 54 | 1.62% |
| Aircraft, ships, and railroad equipment | 17 | 0.51% |
| Precious Metals, Non-Metallic, and Industrial Metal Mining | 5 | 0.15% |
| Coal | 9 | 0.27% |
| Petroleum and Natural Gas | 25 | 0.75% |
| Utilities | 20 | 0.60% |
| Communication | 66 | 1.98% |
| Personal and Business Services | 347 | 10.43% |
| Business Equipment | 69 | 2.07% |
| Business Supplies and Shipping Containers | 29 | 0.87% |
| Transportation | 128 | 3.85% |
| Wholesale | 172 | 5.17% |
| Retail | 308 | 9.26% |
| Restaraunts, Hotels, Motels | 263 | 7.91% |
| Banking, Insurance, Real Estate, Trading | 516 | 15.51% |
| Everything Else | 123 | 3.70% |
| Total | 3,327 | 100.00% |

## TABLE A.2
## BANKRUPTCY DISTRICT DISTRIBUTION

This table gives the full list of 89 bankruptcy districts used in the sample, and the number of sample firms in each district. The two districts in Arkansas share bankruptcy judges, and so are treated as one district in this study. The bankruptcy districts in the Northern Marianas Islands, the Virgin Islands, Guam, and Puerto Rico have been omitted.

| Bankruptcy court | No. of firms | % | Bankruptcy court | No. of firms | % |
|---|---|---|---|---|---|
| Alaska | 5 | 0.15% | Louisiana - East | 21 | 0.63% |
| Alabama - Middle | 13 | 0.39% | Louisiana - Middle | 4 | 0.12% |
| Alabama - North | 22 | 0.66% | Louisiana - West | 22 | 0.66% |
| Alabama - South | 13 | 0.39% | Massachusetts | 63 | 1.89% |
| Arkansas | 23 | 0.69% | Maryland | 59 | 1.77% |
| Arizona | 78 | 2.34% | Maine | 16 | 0.48% |
| California - Central | 181 | 5.44% | Michigan - East | 64 | 1.92% |
| California - East | 38 | 1.14% | Michigan - West | 24 | 0.72% |
| California - North | 71 | 2.13% | Minnesota | 43 | 1.29% |
| California - South | 30 | 0.90% | Missouri - East | 13 | 0.39% |
| Colorado | 59 | 1.77% | Missouri - West | 24 | 0.72% |
| Connecticut | 28 | 0.84% | Mississippi - North | 11 | 0.33% |
| Washington, D.C. | 12 | 0.36% | Mississippi - South | 18 | 0.54% |
| Delaware | 115 | 3.46% | Montana | 6 | 0.18% |
| Florida - Middle | 139 | 4.18% | North Carolina - East | 32 | 0.96% |
| Florida - North | 10 | 0.30% | North Carolina - Middle | 14 | 0.42% |
| Florida - South | 74 | 2.22% | North Carolina - West | 23 | 0.69% |
| Georgia - Middle | 9 | 0.27% | North Dakota | 2 | 0.06% |
| Georgia - North | 107 | 3.22% | Nebraska | 20 | 0.60% |
| Georgia - South | 12 | 0.36% | New Hampshire | 14 | 0.42% |
| Hawaii | 9 | 0.27% | New Jersey | 127 | 3.82% |
| Iowa – North | 6 | 0.18% | New Mexico | 11 | 0.33% |
| Iowa – South | 4 | 0.12% | Nevada | 66 | 1.98% |
| Idaho | 9 | 0.27% | New York - East | 71 | 2.13% |
| Illinois - Central | 12 | 0.36% | New York - North | 35 | 1.05% |
| Illinois - North | 98 | 2.95% | New York - South | 206 | 6.19% |
| Illinois - South | 10 | 0.30% | New York - West | 22 | 0.66% |
| Indiana - North | 31 | 0.93% | Ohio - North | 54 | 1.62% |
| Indiana - South | 53 | 1.59% | Ohio - South | 27 | 0.81% |
| Kansas | 22 | 0.66% | Oklahoma - East | 4 | 0.12% |
| Kentucky - East | 17 | 0.51% | Oklahoma - North | 12 | 0.36% |
| Kentucky - West | 28 | 0.84% | Oklahoma - West | 14 | 0.42% |

**TABLE A.2** – *continued*

| Bankruptcy court | No. of firms | % | Bankruptcy court | No. of firms | % |
|---|---|---|---|---|---|
| Oregon | 12 | 0.36% | Texas - West | 62 | 1.86% |
| Pennsylvania - East | 43 | 1.29% | Utah | 12 | 0.36% |
| Pennsylvania - Middle | 25 | 0.75% | Virginia - East | 56 | 1.68% |
| Pennsylvania - West | 58 | 1.74% | Virginia - West | 13 | 0.39% |
| Rhode Island | 4 | 0.12% | Vermont | 1 | 0.03% |
| South Carolina | 31 | 0.93% | Washington - East | 14 | 0.42% |
| South Dakota | 5 | 0.15% | Washington - West | 49 | 1.47% |
| Tennessee - East | 22 | 0.66% | Wisconsin - East | 13 | 0.39% |
| Tennessee - Middle | 25 | 0.75% | Wisconsin - West | 9 | 0.27% |
| Tennessee - West | 18 | 0.54% | West Virginia - North | 6 | 0.18% |
| Texas – East | 32 | 0.96% | West Virginia - South | 13 | 0.39% |
| Texas – North | 158 | 4.75% | Wyoming | 9 | 0.27% |
| Texas – South | 157 | 4.72% | | | |
| | | | Total | 3,327 | 100.00% |

for each filing in my sample, and keep only one observation per group. This reduces the total number of filings in my sample period to 14,825 separate bankrupt entities. As described in the text, I have full financial information for 3,327 of these filings.

Tables A.1 and A.2 show the distribution of the 3,327 bankruptcies in my final sample across industries and bankruptcy districts.

*A.2.2. Recidivism*

Among dismissed firms in my sample, 7.4% re-file for bankruptcy more than 3 months but less than 3 years after their original filing. An additional 2.0% of dismissed firms re-file within 3 months of their original filing. Meanwhile, 1.6% of reorganized firms re-file within 3 months of their initial filing, and 2.5% re-file between 3 months and 3 years. These recidivism rates are substantially lower than the rate reported by Hotchkiss (1995), who finds that 17.7% of the firms in her sample file a second bankruptcy, but slightly higher (on average across both dismissed and reorganized firms) than the 2.9% rate reported by Chang & Schoar (2007). Differences between the reported refilling rates can likely be attributed to the fact that Hotchkiss (1995) considers a longer period of time post-bankruptcy (generally 5 years) while Chang & Schoar (2007) consider only firms that re-file in the *same* district within 3 years. In addition, Morrison (2005) finds that a significant number of small businesses fail in the first year after bankruptcy without re-filing for bankruptcy. This will depress the observed recidivism rate in my sample and Chang & Schoar (2007), as our samples contain much smaller firms than Hotchkiss (1995). Across all business Chapter 11 filings in LexisNexis from 1990-2011, I find that about 10% of all firms re-file for either Chapter 7 or Chapter 11 bankruptcy at any point after the bankruptcy.

*A.2.3. Bank loan loss accounting*

The results on default costs borne by commercial banks use data obtained from the Consolidated Report of Condition and Income (commonly known as the Call Reports), available from the Federal Financial Institutions Examination Council at https://cdr.ffiec.gov/public/. I measure default costs as the net charge-off rate, defined as

$$NetChargeOffRate_t = \frac{GrossChargeOff_t - Recoveries_t}{\left(\frac{\sum_{k=0}^{3} TotalLoans_{t-k}}{4}\right)},$$

where $k$ indexes quarters. Because charge-offs and recoveries are reported on a year-to-date basis, I only use the financial reports from December of each year (i.e. $t$ pertains only to the 4$^{\text{th}}$ quarter of each year, and the denominator is simply the average reported outstanding loans over each quarterly report in a given year). This gives a total of four observations per bank, one for each year from 2004 through 2007. The denominator uses the average loan balances during the year to account for possible differences in the timing of reported charge-offs and recoveries. Specifically, the accounting standards in FAS 114 state that bad debt should be written off when "it is probable that a creditor will be unable to collect all amounts due according to the contractual terms of the loan agreement." Obviously, there is some discretion in this exact timing, and certainly some of the charge-offs reported at time $t$ correspond to loans that were on the books in previous quarters but, since they have been written off, are no longer recorded at time $t$. Because the amount of total loans is relatively stable across time for most banks, this choice to average across four quarters makes little difference in my estimates. I find essentially identical results if the denominator is total loans at time $t$ or if the average is taken over the previous 6 quarters.

Because banks have some discretion in reporting charge-offs and recoveries, one might be concerned that this affects my measure of default costs. While it likely makes the measure noisier, the difference-in-differences identification should account for biases in a particular direction. Further, it is important to recognize that charge-offs and recoveries have no direct effect on either the income statement or the balance sheet of the bank, which minimizes the incentive for banks to manage these accounts. This is because banks create a loan loss reserve which acts as a contra asset on the balance sheet, and absorbs any net movement in loan losses.

A simple example will illustrate how this works. Suppose that in period 1 a bank disburses $1000 worth of new loans. The bank will expect that some of these loans will default, and will thus provision for loan losses by adding, say, $30 to the loan loss reserve, a contra-asset that reduces the total amount of loans on the balance sheet. This $30 reserve must come out of income in this period; it cannot be deferred until later. Thus, in period 1, the impact of the new lending on the bank's balance sheet and income statement is:

| Assets | |
|---|---|
| Loans | $1,000 |
| Loan loss reserve | ($30) |
| Total | $970 |

| Income | |
|---|---|
| Loan loss provision | ($30) |

In period 2, suppose that $25 worth of lending goes into default, but the bank chooses to wait to see if the default can be cured before it writes off the loans as losses. Then, in this period nothing changes on the balance sheet, but $25 of loans will be reported as non-performing in a separate schedule in the Call Reports.

In period 3 the bank learns that it will only recover $10 of the $25 total of defaulted loans, resulting in a net charge-off of $15. It is this net charge-off that I use in my analysis, rather than the loan loss provision recorded in period 1. Net charge-offs in period 3 do not affect either the balance sheet or the income statement of the bank, since these losses were already accounted for in period 1. Specifically, the $15 loss will reduce the amount of loans but also reduce the contra-asset, so that the new balance sheet will be:

| Assets | | Charge-offs, recoveries, and Non-performing loans | |
|---|---|---|---|
| Loans | $975 | Gross charge-off | $25 |
| Loan loss reserve | ($15) | Recovery | $10 |
| Cash (from recovery) | $10 | Net charge-off | $15 |
| Total | $970 | Non-performing loans | $0 |

Total assets still stand at $970, so recognizing the loss does not affect assets. It also does not affect income in period 3 because the loan losses were provisioned in period 1. Because actual losses are isolated from earnings and assets in this way, bank managers that are seeking to meet earnings expectations will typically do so by managing the provision for loan losses recorded in period 1 rather than actual loan losses. Liu & Ryan (2006) give further detail on the management of loan loss provisions by banks.

### A.3. Robustness checks

In this appendix, I provide results and more detail on the robustness checks described in Section V.G of the text. To be concise, I report regression results only for the three main results of the paper: the probability of reorganization, the recidivism rate, and charge-off rates at commercial banks. All other results are available by request.

*A.3.1. Outliers*

As described in the text, two possible concerns related to outliers are the effects of extremely large firms in the sample and of the business-centric courts of Delaware and the Southern District of New York. Table A.3 reports regression results when these outliers are winsorized. In the case of firm *size*, I winsorize at the 99$^{th}$ percentile, which reduces the mean *size* from $156.7 million to $28.5 million in the sample, but has only a small effect on average ln(*size*). To account for Delaware and the Southern District of New York, I set their non-business caseload share at 54%, equal to the next lowest share in Alaska. Reducing the impact of outliers in this way has no effect on the estimated impact of caseload on bankruptcy outcomes.

**TABLE A.3**
**ROBUSTNESS CHECKS: OUTLIERS**

This table presents robustness checks of my main results after accounting for outliers in either *size* or in the non-business share of caseload. To be succinct, the coefficients on control variables have been omitted from the table, and I only report the results for the probability of being reorganized and of re-filing for bankruptcy within 3 years for dismissed firms. The top four rows of the table repeat the baseline regression results reported in the text of the paper. The next four lines report the coefficients on the main interaction variables when *size* has been winsorized at the 99th percentile. The bottom four rows again re-run the regression models except in these specifications the non-business share of caseload for Delaware and the Southern District of New York has been "winsorized" to 54%, equal to that of Alaska. All specifications are otherwise identical to those presented in the tables in the paper. Standard errors are clustered by bankruptcy district and reported in parenthesis. ***, ** and * indicate statistical significance at 1%, 5%, and 10% level, respectively.

| Model: | | *Reorganized* | | *Re-filed for bankruptcy within 3 years (Dismissed firms)* | |
|---|---|---|---|---|---|
| Baseline | Busy court | 0.149** | 0.087 | 0.368*** | 0.413*** |
| | | (0.061) | (0.068) | (0.131) | (0.130) |
| | Busy court * ln(*size*) | -- | 0.044** | -- | -0.073** |
| | | | (0.022) | | (0.036) |
| Size winsorized at 99th percentile | Busy court | 0.149** | 0.090 | 0.368*** | 0.416*** |
| | | (0.061) | (0.069) | (0.131) | (0.130) |
| | Busy court * ln(*size*) | -- | 0.042* | | -0.076* |
| | | | (0.023) | | (0.039) |
| DE & SDNY winsorized | Busy court | 0.169** | 0.103 | 0.479*** | 0.504*** |
| | | (0.081) | (0.091) | (0.167) | (0.169) |
| | Busy court * ln(*size*) | | 0.081* | | -0.116** |
| | | | (0.046) | | (0.052) |

*A.3.2. Exclusion restriction*

I test for the possibility that three other channels could be biasing my estimates of the impact of caseload on bankruptcy outcomes by allowing time fixed effects to vary by firm size, industry, or geographic region. If firms of a particular size or industry are concentrated in bankruptcy districts with high non-business caseload, my estimates could be biased if these firms changed after BAPCPA for some reason other than differences in judge caseload. Similarly, general regional trends could bias the estimates if bankruptcy districts with high or low non-business caseload are clustered together geographically. The downside of allowing for separate time effects for each of these groups is it drastically reduces the statistical power available due to the inclusion of many more covariates. For example, my main specifications include 30 industry fixed effects and 16 quarter fixed effects (in addition to the 89 bankruptcy district fixed effects), while taking every pairwise combination of these two groups in my data results in a total of 400 industry-quarter fixed effects. Thus, one would expect that statistical power will be somewhat reduced in these specifications.

Table A.4 shows the results with different time effects for each group. In the first set of results, I allow the estimated impact of ln(*size*) to vary of each quarter by including ln(*size*)-by-quarter fixed effects. This does not affect the estimates or statistical significance in any way. Adding industry-by-quarter fixed effects reduces the statistical significance of the effect of caseload on the probability of reorganization ($p$-value=0.13) and the effect of caseload on the probability of re-filing for bankruptcy ($p$-value=0.09). In both cases the coefficient estimates are nearly identical to my main specifications, indicating that the loss of significance is due only to the reduced statistical power in these robustness checks. Aside from these two estimates, all other coefficients retain statistical significance and are essentially unchanged with the inclusion of industry-quarter fixed effects. Finally, I use the region of the country that each bankruptcy district lies in to create region-by-time fixed effects. Regions are defined by the U.S. Census into nine groups: New England, Middle Atlantic, East North Central, West North Central, South Atlantic, East South Central, West South Central, Mountain, and Pacific.[3] These fixed effects account for any clustering of consumer-centric districts by using only variation within each region to identify the impact of BAPCPA on caseload. Including separate time fixed effects for each region does not affect my estimates in any significant way.

Table A.5 runs similar robustness checks on the commercial bank regressions. Here I again allow for varying time effects by the size of the bank and by the region that the bank is located in. For banks with branches in multiple regions, I use the state in which the largest portion of the bank's deposits are located to identify the census region it belongs to. The inclusion of these additional controls does not affect my results.

[3] The list at https://www.census.gov/geo/www/us_regdiv.pdf shows exactly which states lie in each region.

## TABLE A.4
## ROBUSTNESS CHECKS: EXCLUSION RESTRICTION

This table presents robustness checks of my main results with the inclusion of time fixed effects that differ for groups of bankruptcy filings. To be succinct, the coefficients on control variables have been omitted from the table, and I only report the results for the probability of being reorganized and of re-filing for bankruptcy within 3 years. The top four rows of the table repeat the baseline regression results reported in the text of the paper. The next four lines report the coefficients on the main interaction variables when ln(*size*)-by-time fixed effects have been included in the set of controls. The next four rows present results when separate time fixed effects are included for each of the 30 industries. The bottom four rows contain results when separate time effects have been included for each the 9 census divisions: New England, Middle Atlantic, East North Central, West North Central, South Atlantic, East South Central, West South Central, Mountain, and Pacific. All specifications are otherwise identical to those presented in the tables in the paper. Standard errors are clustered by bankruptcy district and reported in parenthesis. ***, ** and * indicate statistical significance at 1%, 5%, and 10% level, respectively.

| Model: | | *Reorganized* | | *Re-filed for bankruptcy within 3 years (Dismissed firms)* | |
|---|---|---|---|---|---|
| Baseline (135 total fixed effects) | Busy court | 0.149** | 0.087 | 0.368*** | 0.413*** |
| | | (0.061) | (0.068) | (0.131) | (0.130) |
| | Busy court * ln(*size*) | -- | 0.044** | -- | -0.073** |
| | | | (0.022) | | (0.036) |
| Size X time fixed effects (16 additional fixed effects) | Busy court | 0.159** | 0.044 | 0.395*** | 0.352** |
| | | (0.069) | (0.081) | (0.144) | (0.148) |
| | Busy court * ln(*size*) | -- | 0.053** | -- | -0.059* |
| | | | (0.023) | | (0.032) |
| Industry X time fixed effects (354 additional fixed effects) | Busy court | 0.104 | 0.029 | 0.298** | 0.356** |
| | | (0.069) | (0.076) | (0.144) | (0.141) |
| | Busy court * ln(*size*) | -- | 0.049* | -- | -0.101** |
| | | | (0.025) | | (0.047) |
| Region X time fixed effects (144 additional fixed effects) | Busy court | 0.213*** | 0.168** | 0.422** | 0.460*** |
| | | (0.069) | (0.083) | (0.163) | (0.167) |
| | Busy court * ln(*size*) | -- | 0.030 | -- | -0.075** |
| | | | (0.021) | | (0.035) |

## TABLE A.5
## ROBUSTNESS CHECKS: EXCLUSION RESTRICTION ON BANK DATA

This table presents robustness checks of my main results that examine the effect of caseload on bank charge-offs. In these regressions, I allow for time fixed effects that vary by the size or geographic region of the bank. To be succinct, the coefficients on control variables have been omitted from the table, and I only report the results for the probability of being reorganized and of re-filing for bankruptcy within 3 years. The top four rows of the table repeat the baseline regression results reported in the text of the paper. The next four lines report the coefficients on the main interaction variables when ln(*size*)-by-time fixed effects have been included in the set of controls. The bottom four rows contain results when separate time effects have been included for each the 9 census division: New England, Middle Atlantic, East North Central, West North Central, South Atlantic, East South Central, West South Central, Mountain, and Pacific. All specifications are otherwise identical to those presented in the tables in the paper. Standard errors are clustered by commercial bank and reported in parenthesis. ***, ** and * indicate statistical significance at 1%, 5%, and 10% level, respectively.

| Model: | | *Net charge-offs on C&I loans (% of total C&I loans)* | |
|---|---|---|---|
| Baseline | Busy court | 0.437** | 1.151 |
| | | (0.194) | (0.729) |
| | Busy court * ln(*size*) | -- | -0.127 |
| | | | (0.120) |
| Ln(assets) X time fixed effects | Busy court | 0.432** | 1.147 |
| (4 additional fixed effects) | | (0.194) | (0.729) |
| | Busy court * ln(*size*) | -- | -0.128 |
| | | | (0.120) |
| Region X time fixed effects | Busy court | 0.403* | 0.929 |
| (36 additional fixed effects) | | (0.218) | (0.745) |
| | Busy court * ln(*size*) | -- | -0.093 |
| | | | (0.121) |

### *A.3.3. Alternative measures of bank loan losses*

In the text of the paper, I scale net charge-offs by the average total outstanding amount of lending during the year as a measure of bank loan losses. Scaling net charge-offs by total loans means that this charge-off rate is roughly equivalent to the probability of default times the loss given default for a particular loan:

$$NetChargeOffRate_t \approx PD_t \times LGD_t$$

One would expect that busy bankruptcy courts principally impact $LGD_t$ rather than $PD_t$, and therefore it would be ideal to measure $LGD_t$ alone for each bank by scaling net charge-offs by the amount of *defaulted* loans rather than scaling by *total* loans. In practice, however, matching charge-offs directly to loans that are in default is impossible using Call Report data. In each quarter, banks report their year-to-date charge-offs and recoveries as well as the current balance of "non-performing" loans – loans that are over 90-days past-due or non-accruing – which I use as a measure of total defaulted loans. However, the reported net charge-offs in quarter $t$ could be related to loans that were non-performing in some previous quarter. Thus, scaling net charge-offs by non-performing loans from period $t$ gives an incorrect estimate of $LGD_t$, but it is unclear how to combine the non-performing loan data from previous quarters to get a better measure. For example, the following is data from an actual bank in my sample:

**TABLE A.6**
**EXAMPLE BANK DATA**

| *Date* | *Year-to-date Net C&I Loan Charge-offs* | *Non-performing C&I Loans* | *Total Outstanding C&I Loans* | *Net Charge-off Rate* | *LGD1* | *LGD2* |
|---|---|---|---|---|---|---|
| 2005q1 | -22 | 244 | 35460 | | | |
| 2005q2 | 103 | 121 | 34840 | | | |
| 2005q3 | 117 | 501 | 31225 | | | |
| 2005q4 | 211 | 353 | 33249 | 0.63% | 69.24% | 42.12% |
| 2006q1 | 101 | 286 | 31102 | | | |
| 2006q2 | 170 | 232 | 31640 | | | |
| 2006q3 | 145 | 320 | 31234 | | | |
| 2006q4 | 263 | 81 | 29666 | 0.85% | 114.47% | 82.19% |

In aggregate, this bank lost $211,000 in bad debt in 2005. The net charge-off rate used in the text of the paper (displayed in the fifth column) is calculated by scaling this amount by the average of total outstanding C&I loans for the year, in this case $33.7 million, giving a total charge-off rate of 0.63% in 2005. Because total loans are fairly stable over time, this is likely a close estimate of the true $PD_t \times LGD_t$ for that year. Estimating $LGD_t$ by itself is not straightforward because the level of non-performing loans fluctuates widely over time and charge-offs are not matched directly to non-performing loans. The table above gives two possible alternatives. $LGD1$ is calculated by dividing end-of-year net charge offs by the average of non-performing loans over the year, e.g. 211 / 304.75 in 2005. This is similar to how $NetChargeOffRate$ is calculated, but it has the drawback of being very volatile. For example, $LGD1$ in

2006 is greater than 100%, which logically doesn't make sense and is likely because the bank wrote off a large portion of loans in late 2006, leaving a low non-performing loan balance at the end of the year but high net charge-offs. $LGD2$ alleviates this problem to some extent by scaling net charge-offs instead by the maximum of non-performing loans during the year, e.g. 211 / 501 in 2005 and 263 / 320 in 2006. This measure has the advantage of ignoring low values of non-performing loans, which in most cases gives a more accurate estimate of the true loss given default since non-performing loans decrease after charge-offs are recognized.

Importantly, neither $LGD1$ or $LGD2$ is likely to be a biased measure of loss given default, only noisy. Accordingly, Table A.7 presents regressions similar to those in Table 1.11 in the text of the paper except it uses these two alternative definitions of loss given default as the dependent variable. As in the text of the paper, all bank variables are winsorized at the 1st and 99th percentile to account for outliers, an adjustment that is particularly important for the noisy measures of loss given default. The regressions show that these two alternative measures of credit losses produce nearly identical results to those in Table 1.11, although the statistical significance of $LGD1$ and $LGD2$ is slightly lower because they are less precisely measured. Specifically, a 306-hour increase in caseload is estimated to increase $LGD1$ by 37 percentage points, a 46% increase relative to its mean value of 80 percent. As measured by $LGD2$, the same shock to caseload increases losses by 19 percentage points, a 52% rise relative to its mean of 36 percent. Thus, the impact of a 306-hour rise in caseload by any of the three measures of credit losses is close to a 50% increase relative to the mean loss amount.

One interesting point that comes from using $LGD_t$ rather than overall credit losses is that it appears that small banks experience the largest credit losses when bankruptcy courts become busy. In the main regressions in Table 1.11, I do not find any differential effects for large and small banks. If it is indeed the case that small banks are most affected by crowded courts, this mirrors the fact that larger debtors are able to sway the courts in their favor when judges are busy. Similarly, these findings suggest that large banks may be able to lobby the busy judge or otherwise mitigate the effects of crowded courts.

## TABLE A.7
## ALTERNATIVE MEASURES OF BANK CREDIT LOSSES

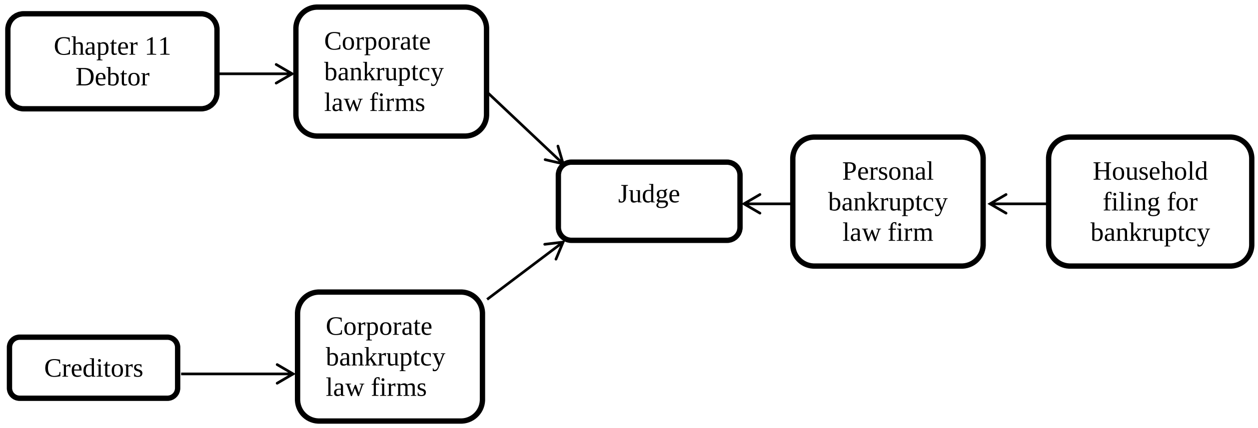
This table repeats the regressions of Table 1.11 in the text of the paper using two alternative measures of credit losses. In the first three columns the dependent variable is net C&I loan charge-offs scaled by the average balance of non-performing C&I loans reported by the bank during that year. The last three columns scale net charge-offs by the maximum reported non-performing C&I loan balance during the year. Control variables are defined as in Table 1.8 in the paper, except *net charge-off rate on all other loans* is defined similarly to the dependent variable—e.g. it is scaled by average or maximum non-performing loans. All regressions include fixed effects for the 6,896 banks included in the sample as well as year fixed effects. All models are estimated by OLS. Standard errors are clustered by commercial bank and reported in parenthesis. ***, ** and * indicate statistical significance at 1%, 5%, and 10% level, respectively.

| | Net charge-offs on C&I loans | | | | | |
|---|---|---|---|---|---|---|
| *Dependent Variable:* | *% of average non-performing C&I loans (LGD1)* | | | *% of maximum non-performing C&I loans (LGD2)* | | |
| Busy court | 90.657* | 66.978 | 379.329*** | 43.887** | 34.219* | 144.768*** |
| | (49.823) | (51.958) | (130.927) | (19.264) | (20.065) | (50.414) |
| Busy court * ln(Assets) | -- | -- | -53.182*** | -- | -- | -18.806** |
| | | | (19.620) | | | (7.568) |
| Post BAPCPA * ln(Assets) | -- | -- | -36.649** | -- | -- | -12.209** |
| | | | (15.523) | | | (5.969) |
| Asset growth | -6.987 | 2.415 | 4.178 | -10.731 | -6.518 | -5.677 |
| | (21.894) | (22.002) | (21.990) | (8.479) | (8.498) | (8.485) |
| Net charge-off rate on all other loans | 0.048 | 0.049 | 0.049 | 0.034 | 0.034 | 0.035 |
| | (0.041) | (0.041) | (0.041) | (0.030) | (0.030) | (0.030) |
| Ln(per captia income) | -- | 81.824 | 56.997 | -- | 23.156 | 10.648 |
| | | (126.359) | (127.450) | | (50.522) | (51.057) |
| Ln(population) | -- | -258.819 | -285.763 | -- | -65.803 | -78.252 |
| | | (180.676) | (180.858) | | (79.089) | (79.284) |
| Unemployment rate | -- | 6.462 | 6.718 | -- | 2.037 | 2.257 |
| | | (7.168) | (7.212) | | (2.796) | (2.808) |
| House price appreciation | -- | -190.139*** | -170.195** | -- | -84.947*** | -73.727*** |
| | | (65.335) | (66.715) | | (26.195) | (26.619) |
| Fixed effects: | | | | | | |
| Bank | Yes | Yes | Yes | Yes | Yes | Yes |
| Year | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 22,008 | 22,008 | 22,008 | 22,008 | 22,008 | 22,008 |
| R-squared | 0.001 | 0.002 | 0.002 | 0.001 | 0.002 | 0.003 |

## FIGURE A.1

### PARTIES INVOLVED IN BANKRUPTCY

This schematic depicts the various parties involved in bankruptcy courts and how they interact with the bankruptcy judge. When BAPCPA passed, it dramatically reduced the number of household bankruptcy filings, on the right. This feeds through to the judge, who is left with a far lighter docket, while the corporations, creditors, and corporate law firms remain relatively unaffected by the law.



# B

# Appendix to Chapter 2

## B.1. Details of data received from claims administrators

Data for the study were made available by four leading providers of restructuring and insolvency administrative services: BMC Group, EPIQ Bankruptcy Solutions, Donlin Recano & Company, and Kurtzman Carson Consultants (KCC). These firms made available to us an electronic version of the claims register, voting tabulations, and claims transfers for each bankruptcy. The information from each administrator was largely the same and compiling it together is unlikely to bias our results. However, the format of the data varies for each provider. Below we illustrate details of the different data formats and how we identify if a given claim was allowed to vote, if it was transferred in bankruptcy, and if a given claimholder was a trustee for public bond-holders.

### *B.1.1.BMC Group (43 bankruptcy cases; 36 cases with complete register and tabulation data)*

For each bankruptcy case, BMC Group provided data that contained information from the credit register ($t_1$), voting tabulations ($t_2$) and transfers in one consolidated dataset. There are two BMC cases for which no register data was received, and five cases with no tabulation data. So we can unambiguously track each claim from $t_1$ to $t_2$ for 36 cases. The following is a simple example of what the data actually looks like:

**TABLE B.1**
**EXAMPLE BMC DATA**

| Creditor | Amount | Claim type | Transferee | Voting plan class | Amount accepting | Amount rejecting | Amount abstaining |
|---|---|---|---|---|---|---|---|
| Fleet National Bank | $150,000 | Secured | | | | | |
| Nelson, Arthur | $58,000 | Unsecured | Sierra Liquidity Fund | 5 | $58,000 | | |
| The Bank of New York as trustee | $1,600,000 | Unsecured | | 5 | $980,000 | $600,000 | $20,000 |

In this example, Fleet National's claim was not transferred nor was it allowed to vote. Arthur Nelson's claim of $58,000 was sold to Sierra Liquidity Fund. This claim was allowed to vote on the plan of reorganization as part of voting class 5. We use information from the disclosure statement filed with the court to determine what types of claims constitute this voting class (e.g., general unsecured claims).

The Bank of New York claim illustrates a case in which the bank is acting as a custodian. We identify these cases by searching in the creditor name for the terms "trustee" and "custodian" (or abbreviations of these). In addition, we identified trustees of public bond issues by examining the disclosure statements which typically outline the basic pre-petition capital structure of the debtor. Also note that since this claim represents multiple public bonds, portions of the claim can accept, reject, and abstain from voting, depending on how each bondholder reported his vote to the Bank of New York.

*B.1.2. Donlin Recano & Company (10 bankruptcy cases)*

Simlar to BMC Group, Donlin Recano provided data in a single dataset for each case. However, Donlin Recano only provided information on claims that were permitted to vote (i.e., in our example, Donlin Recano records would be missing Fleet National Bank).

*B.1.3. EPIQ Bankruptcy Solutions (52 bankruptcy cases)*

The data provided by EPIQ came in two datasets, the claims register and the voting tabulation. Claim trading was tracked within the register as in the following example:

**TABLE B.2**
**EXAMPLE EPIQ REGISTER DATA**

| Creditor | Amount | Claim type |
|---|---|---|
| Fleet National Bank | $150,000 | Secured |
| Nelson, Arthur fully transferred to: Sierra Liquidity Fund | $58,000 | Unsecured |
| The Bank of New York as trustee | $1,600,000 | Unsecured |

To determine whether a claim was traded, we searched for the term "transferred" in the creditor name and/or address. Based on the search results we created a record of buyers and sellers. This record is additionally cross-checked with the information in the voting-tabulation file as the transferred claims only show the name of the claim buyer. Using the same example, a voting tabulation from EPIQ would look like:

**TABLE B.3**
**EXAMPLE EPIQ TABULATION DATA**

| Creditor | Amount | Voting plan class | Amount accepting | Amount rejecting | Amount abstaining |
|---|---|---|---|---|---|
| Sierra Liquidity Fund | $58,000 | 5 | $58,000 | | |
| The Bank of New York as trustee | $1,600,000 | 5 | $980,000 | $600,000 | $20,000 |

From this example, we also see that Fleet National Bank's claim does not appear in the voting tabulations. This enables us to conclude that Fleet's claim was not allowed to vote. There is no unique identifier that would allow us to merge the tabulation to the credit register. We merge the two sets together by creditor name and claim amount. This procedure however is not without caveats because creditor names are not always consistent between the two datasets, claim amounts can change somewhat (e.g. due to accrued interest, or portions of claims that are disallowed), and the presence of multiple claims held by the same creditor of the same amount.

*B.1.4. Kurtzman Carson Consultants (31 bankruptcy cases)*

KCC provided us with three datasets for each case identifying claims at register, voter tabulation, and a list of transferred claims. The claims register and voter tabulations look very similar to those provided by EPIQ, except that the claims register contains no information on whether a claim was transferred, since this information is kept in the third dataset. Again there is no unique identifier that allows us to match the three datasets together, and inconsistencies in names and amounts could potentially introduce an error in matching.

While we received our data privately in an easily readable electronic format, all of the data are also available publically in flat-text or scanned-text format through the U.S. Public Access to Court Electronic Records (PACER) system of bankruptcy filings, the disclosure of which is regulated by the Federal Rules of Bankruptcy Procedure. All documents disclosed in a bankruptcy filing—including the schedules of assets and liabilities, and voting tabulations—are public information and can be accessed on-line using PACER This makes PACER an immensely rich source of information. However, data from filings are not organized in any way that allows for easy assimilation, and instead are stored as separate PDF files numbered according to how and when they appear in the court docket. As a result, there are thousands of scanned documents per case, and there is no other way of finding the relevant information, but by individually reviewing each one of these files. For example, to give a sense of how the list of files could grow very rapidly, each filing of a 3001(e) proof of claim transfer would be entered as a separate document, as would any filing that would be object to the transfer. Although the docket is easily searchable and provides short descriptions of each filing, for our analysis, which relies on identification of individual creditors and detailed bankruptcy outcomes, we actually need the access to the documents.

# TABLE B.4
## LIST OF BANKRUPTCY CASES IN THE SAMPLE

This table lists the 136 bankrupt firms in our sample and provides information on the bankruptcy, including the filing and exit dates, size at filing, the bankruptcy outcome, and the identification and role of hedge fund involvement in the bankruptcy. The debtors are grouped by their single-digit SIC code and sort chronologically by filing date with the groupings. *Assets at filing* is the self-reported asset size of the firm, recorded on the voluntary petition for Chapter 11 protection. *Outcome* references whether the firm is reorganized within Chapter 11, sold as a going-concern to a financial or strategic buyer, or liquidated piecemeal. *Hedge funds (our data)* indicates whether we observe hedge fund holdings in the debtor at the filing of the schedules of assets and liabilities ($t_1$), or at the tabulation of votes on a plan of reorganization ($t_2$), or both. *Hedge funds (public sources)* lists the hedge funds involved in the case if a public source, such as *The Deal Pipeline* or the bankruptcy disclosure statement, identifies the hedge fund. *Hedge funds' role (public sources)* uses the same public source to group the stated role of the hedge funds in the case into whether the hedge fund was the acquirer in a 363 sale, a controlling equity owner upon exiting a Chapter 11 reorganization, a DIP lender, a provider of debt financing upon exiting a Chapter 11 reorganization, or a provider of equity financing through a rights offering upon exiting a Chapter 11 reorganization.

| Filing Date | Debtor | Assets at filing ($US Millions) | Pre-pack | Exit Date | Outcome | Hedge funds (our data) | Hedge funds (public sources) | Hedge funds' role (public sources) |
|---|---|---|---|---|---|---|---|---|
| Mining & construction: | | | | | | | | |
| 11/13/2002 | Horizon Natural Resources | -- | | 9/30/2004 | Sold to financial buyer | $t_1$, $t_2$ | W.L. Ross & Co. | Acquirer in 363 sale |
| 9/25/2003 | JA Jones | -- | | 8/18/2004 | Liquidated | -- | -- | -- |
| 10/29/2006 | I E Liquidation/Ideal Electric | $22.60 | | 5/26/2007 | Sold to strategic buyer | $t_1$, $t_2$ | -- | -- |
| 12/12/2008 | CDX Gas | $500.00 | | 9/22/2009 | Reorganized | $t_2$ | -- | -- |
| Manufacturing: | | | | | | | | |
| 4/2/2001 | W.R. Grace & Co. | $2,584.90 | | -- | In process | $t_1$, $t_2$ | -- | -- |
| 6/28/2001 | 360 Networks | $6,326.00 | | 11/12/2002 | Reorganized | $t_2$ | W.L. Ross & Co. | Controlling investor at exit |
| 11/2/2001 | General Datacomm Ind. | $64.00 | | 9/15/2003 | Reorganized | $t_2$ | Ableco Finance (Cerberus) | Exit debt financing |
| 12/5/2001 | Hayes Lemmerz Intern. | $2,800.00 | | 6/3/2003 | Reorganized | $t_1$ | Apollo Management | Controlling investor at exit |
| 3/12/2002 | Zenith Industrial | $166.00 | | 5/22/2002 | Sold to financial buyer | -- | Questor Management | Acquirer in 363 sale |
| 3/13/2002 | Guilford Mills | $551.10 | Yes | 9/30/2002 | Reorganized | -- | -- | -- |
| 4/15/2002 | Exide | $2,100.00 | | 5/5/2004 | Reorganized | $t_2$ | R2 Top Hat, Silver Oak | Controlling investor at exit |
| 5/31/2002 | Farmland | $2,700.00 | | 5/1/2004 | Liquidated | $t_1$ | -- | -- |
| 6/8/2002 | DESA Holdings | $235.00 | | 4/1/2005 | Sold to financial buyer | $t_1$, $t_2$ | H.I.G. Capital Management | Acquirer in 363 sale |
| 11/15/2002 | Oakwood Homes | $812.00 | Yes | 4/20/2004 | Sold to financial buyer | $t_2$ | Greenwich Capital Markets, Ranch Capital, Berkshire Hathaway | DIP lender |
| 5/19/2003 | Weirton Steel | $696.00 | | 8/24/2004 | Sold to financial buyer | -- | W.L. Ross & Co. | Acquirer in 363 sale |
| 7/15/2003 | Loral Space Communications | $2,654.00 | | 11/21/2005 | Reorganized | $t_1$ | -- | -- |
| 8/20/2003 | Ddi Corp. | $203.00 | Yes | 12/12/2003 | Reorganized | $t_2$ | Symphony Asset Management, Courage Capital, Pacific Edge Investment | Controlling investor at exit |
| 8/26/2003 | Met-Coil Systems | $50.00 | | 10/19/2004 | Reorganized | -- | -- | |
| 3/31/2004 | Dan River | $441.80 | | 2/14/2005 | Reorganized | $t_1$, $t_2$ | Ableco Finance (Cerberus) | Exit debt financing |
| 9/1/2004 | Techneglas | $100.00 | | 11/1/2005 | Reorganized | $t_1$, $t_2$ | -- | -- |
| 9/3/2004 | Quigley (Pfizer Sub) | $155.20 | | -- | Liquidated | -- | -- | -- |
| 12/16/2004 | Tropical Sportwear | $247.10 | | 5/17/2005 | Sold to strategic buyer | -- | -- | -- |
| 5/17/2005 | Collins & Aikman Corp | $3,196.70 | | 10/12/2007 | Liquidated | $t_1$, $t_2$ | -- | -- |

## **TABLE B.4** – *continued*

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| 7/26/2005 | Protocol Services | $140.50 | | 1/1/2006 | Reorganized | $t_2$ | Bayside Recovery | Controlling investor at exit |
| 12/1/2005 | Nobex Corp. | $10.00 | | 10/11/2006 | Sold to strategic buyer | -- | -- | -- |
| 2/10/2006 | JL French | $341.40 | Yes | 6/30/2006 | Reorganized | $t_1$ | -- | -- |
| 3/3/2006 | Dana Corporation | $7,900.00 | | 2/1/2008 | Reorganized | $t_1$, $t_2$ | Centerbrige Partners, Avenue Capital, Silver Point, Quadrangle | Equity rights offering participant, controlling investor at exit |
| 4/10/2006 | Global Home Products | $472.50 | | 2/15/2008 | Reorganized | $t_2$ | Global Home Product Investors (Cerberus) | Controlling investor at exit |
| 7/27/2006 | Source Enterprises | $4.30 | | 10/2/2007 | Reorganized | -- | Greenwich Street Corporate Growth Partners | DIP lender, controlling investor at exit |
| 8/17/2006 | Weld Wheel Industries | $31.70 | | 6/5/2007 | Sold to strategic buyer | -- | -- | -- |
| 8/21/2006 | Radnor Holdings | $361.50 | | 11/29/2006 | Sold to financial buyer | $t_1$, $t_2$ | Silver Point Capital, Tennenbaum Capital Partners | DIP lender, controlling investor at exit |
| 8/31/2006 | Portrait Corporation of America | $153.20 | | 7/17/2007 | Sold to strategic buyer | -- | -- | -- |
| 9/20/2006 | CEP Holdings | $20.00 | | 5/27/2007 | Liquidated | -- | -- | -- |
| 10/30/2006 | Dura Automotive Systems | $1,990.00 | | 6/27/2008 | Reorganized | $t_1$, $t_2$ | Blackstone Distressed Securities/GSO Capital Partners, Pacificor | Exit debt financing, controlling investor at exit |
| 1/29/2007 | PT Holdings Company | $153.70 | | 8/28/2007 | Reorganized | $t_1$, $t_2$ | Golden Tree Asset Management, Catalyst Investment, Delaware Investment Company | DIP lender, equity rights offering, controlling investor at exit |
| 8/16/2007 | Quaker Fabric | $155.20 | | 8/27/2008 | Liquidated | $t_1$ | GB Merchant Partners | DIP lender |
| 11/9/2007 | Levitt and Sons | $411.00 | | 2/20/2009 | Liquidated | $t_1$ | -- | -- |
| 1/7/2008 | Heartland Automotive | $334.00 | | 1/16/2009 | Reorganized | -- | Quad C Partners | Controlling investor at exit |
| 1/28/2008 | American LaFrance | $189.00 | | 7/23/2008 | Reorganized | $t_1$ | Patriarch Partners | DIP lender, exit debt financing, controlling investor at exit |
| 2/22/2008 | Wellman | $124.30 | | 1/31/2009 | Reorganized | $t_2$ | Sola | Exit debt financing, controlling investor at exit |
| 3/5/2008 | Ziff Davis Media | $313.00 | Yes | 7/1/2008 | Reorganized | $t_1$, $t_2$ | -- | -- |
| 3/16/2008 | Shapes-Arch Holdings | $0.10 | | 8/8/2008 | Sold to financial buyer | $t_1$ | H.I.G. Capital Management | Acquirer in 363 sale |
| 3/30/2008 | AMPEX Corporation | $26.50 | Yes | 10/3/2008 | Reorganized | $t_1$, $t_2$ | Hillside Capital | Exit debt financing, controlling investor at exit |
| 4/4/2008 | Sturgis Iron & Metal Co. | $23.40 | | 5/4/2009 | Liquidated | -- | -- | -- |
| 4/23/2008 | Kimball Hill | $795.50 | | 3/24/2009 | Liquidated | $t_1$ | -- | -- |
| 7/8/2008 | Syntax-Brillian Corporation | $175.70 | | 7/7/2009 | Liquidated | -- | Silver Point Capital | DIP lender |
| 7/15/2008 | Pierre Foods | $304.20 | | 12/12/2008 | Reorganized | $t_2$ | Oaktree Capital Management | DIP lender, controlling investor at exit |
| 8/27/2008 | NetEffect | $1.00 | | 6/1/2009 | Sold to strategic buyer | $t_1$, $t_2$ | -- | -- |
| 11/13/2008 | The Antioch Company | $66.40 | Yes | 2/6/2009 | Reorganized | -- | -- | -- |
| 12/30/2008 | Constar International | $420.00 | Yes | 5/29/2009 | Reorganized | -- | -- | -- |
| 1/2/2009 | Recycled Paper Greetings | $100.00 | Yes | 2/24/2009 | Sold to strategic buyer | $t_1$ | -- | -- |
| 2/21/2009 | Journal Register Company | $142.20 | Yes | 8/7/2009 | Reorganized | $t_2$ | -- | -- |
| 3/16/2009 | Masonite Corporation | $1,527.50 | Yes | 6/9/2009 | Reorganized | -- | -- | -- |
| Services: | | | | | | | | |
| 7/19/1998 | FPA Medical | $831.20 | Yes | 6/1/1999 | Sold to strategic buyer | -- | -- | -- |
| 11/27/2002 | Genuity | $1,940.00 | Yes | 2/4/2003 | Sold to strategic buyer | -- | -- | -- |

**TABLE B.4** – *continued*

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| 1/19/2005 | American Banknote Corp | $124.70 | Yes | 4/8/2005 | Reorganized | -- | Bay Harbour Investments, Highland Capital Management | Controlling investor at exit |
| 2/18/2005 | Access Cardiosystems | $10.00 | | 5/25/2007 | Reorganized | -- | -- | -- |
| 5/31/2005 | WATTS Health Foundation | $54.80 | | 5/2/2007 | Sold to strategic buyer | $t_1$, $t_2$ | -- | -- |
| 7/5/2005 | St. Vincent's Medical Centers | $971.90 | | 8/31/2007 | Reorganized | $t_1$, $t_2$ | -- | -- |
| 9/30/2005 | The Brooklyn Hospital | $233.00 | | 10/23/2007 | Reorganized | $t_2$ | -- | -- |
| 4/16/2007 | Bayonne Medical Center | $88.00 | | 2/1/2008 | Sold to strategic buyer | -- | -- | -- |
| 1/23/2008 | PRC | $354.00 | Yes | 6/30/2008 | Reorganized | $t_2$ | Silver Point Capital, Bayside Capital, and Babson Capital | Exit debt financing, controlling investor at exit |
| 2/14/2008 | Charys Holding | $245.00 | Yes | 3/12/2009 | Reorganized | $t_1$, $t_2$ | -- | -- |
| 3/10/2008 | Terisa Systems | $12.00 | Yes | 5/5/2008 | Reorganized | -- | -- | -- |
| 3/11/2008 | Louisiana Riverboat Gaming | $250.40 | | 6/17/2009 | Reorganized | $t_2$ | -- | -- |
| 5/5/2008 | Tropicana Entertainment | $2,840.00 | | 7/1/2009 | Reorganized | $t_1$ | Silver Point Capital, Icahn Capital | DIP lender, exit debt financing, controlling investor at exit |
| 7/7/2008 | National Dry Cleaners | $0.50 | | 5/31/2009 | Liquidated | -- | -- | -- |
| 1/12/2009 | Apex Silver Mines | $721.30 | Yes | 3/24/2009 | Reorganized | $t_2$ | Gilder, Gagnon, and Howe Co., Sentient Executive Group | Controlling investor at exit |
| Transportation, communication, and utilities: | | | | | | | | |
| 5/21/2001 | Teligent | $1,200.00 | | 9/12/2002 | Reorganized | -- | -- | -- |
| 11/13/2001 | ANC Rental | $6,497.50 | | 4/6/2004 | Sold to financial buyer | -- | Cerberus Capital Partners | Acquirer in 363 sale |
| 1/28/2002 | Global Crossing | $22,400.00 | | 12/9/2003 | Sold to strategic buyer | $t_1$, $t_2$ | -- | |
| 12/19/2002 | Focal Communications | $561.00 | | 7/7/2003 | Reorganized | $t_1$, $t_2$ | Madison Dearborn, Frontenac | Controlling investor at exit |
| 3/14/2003 | TWI | -- | | 5/27/2005 | Liquidated | $t_1$ | -- | -- |
| 6/19/2003 | Touch America | $1,608.10 | | 10/4/2004 | Liquidated | $t_2$ | -- | -- |
| 7/8/2003 | National Energy & Gas | $7,613.00 | | 10/29/2004 | Reorganized | $t_1$, $t_2$ | -- | -- |
| 7/8/2003 | USGEN New England | $2,337.40 | | 6/1/2005 | Liquidated | $t_1$, $t_2$ | -- | -- |
| 9/14/2003 | Northwestern Corporation | $2,624.90 | | 11/1/2004 | Reorganized | $t_1$, $t_2$ | -- | -- |
| 9/12/2004 | US Airways | $8,806.00 | | 9/27/2005 | Sold to strategic buyer | -- | Wellington Management, Par Investment Partners, Peninsula Investment, Tudor Investment | Exit debt financing, equity rights participant |
| 9/14/2005 | Delta Air Lines | $21,561.00 | | 4/30/2007 | Reorganized | $t_1$, $t_2$ | -- | -- |
| 9/14/2005 | Northwest Airlines | $14,352.00 | | 5/31/2007 | Reorganized | $t_1$, $t_2$ | -- | -- |
| 9/23/2005 | Entergy New Orleans | $703.20 | | 5/8/2007 | Reorganized | $t_2$ | -- | -- |
| 11/7/2005 | FLYi/Atlantic Coast Airlines | $378.50 | | 3/30/2007 | Liquidated | -- | -- | -- |
| 12/20/2005 | Calpine Corporation | $26,628.80 | | 1/31/2008 | Reorganized | $t_1$ | Harbinger Capital | Controlling investor at exit |
| 1/25/2006 | Leaseway Motorcar Transport | $177.70 | | 1/29/2007 | Reorganized | $t_2$ | Yucaipa Cos. | Controlling investor at exit |
| 10/15/2006 | Sea Containers | $1,700.00 | | 2/11/2009 | Reorganized | $t_1$, $t_2$ | Dune Capital, Trilogy Capital, Caspian Capital Partners | DIP lender |
| 10/15/2007 | Kitty Hawk | $40.00 | | 7/9/2008 | Liquidated | $t_1$ | Laurus Master Fund | DIP lender |
| 11/8/2007 | SN Liquidation | $97.00 | Yes | 10/22/2008 | Sold to financial buyer | -- | Versa Capital Management | DIP lender, controlling investor at exit |
| 11/19/2007 | Performance Transport | $20.50 | | 7/14/2008 | Liquidated | -- | Black Diamond Capital | DIP lender |
| 12/24/2007 | Maxjet | $14.80 | | 8/13/2009 | Liquidated | -- | -- | -- |
| 4/2/2008 | ATA Airlines | $250.40 | | 3/31/2009 | Liquidated | $t_1$ | -- | -- |
| 4/5/2008 | Skybus Airlines | $100.00 | | 4/17/2009 | Liquidated | $t_1$ | -- | -- |

## TABLE B.4 – *continued*

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| 4/26/2008 | EOS Airlines | $70.20 | | 2/18/2009 | Liquidated | -- | -- | -- |
| Wholesale & retail trade: | | | | | | | | |
| 10/12/2001 | Polaroid Corp. | $1,800.00 | | 7/31/2002 | Sold to financial buyer | -- | Wingate Partners, One Equity Partners | DIP lender, controlling investor at exit |
| 12/2/2001 | Enron | $24,700.00 | | 11/17/2004 | Sold to strategic buyer | $t_1$ | | |
| 1/22/2002 | Kmart | $16,287.00 | | 5/6/2003 | Reorganized | $t_1$, $t_2$ | ESL Investments, Third Avenue Trust | Equity rights offering participant, controlling investor at exit |
| 10/1/2002 | Agway | $1,574.40 | | 5/3/2004 | Liquidated | -- | | |
| 1/31/2003 | American Commercial Lines | $838.90 | | 1/11/2005 | Reorganized | $t_1$, $t_2$ | HY I Investments (Sam Zell | Controlling investor at exit |
| 4/1/2003 | Fleming Companies | $4,200.00 | | 8/23/2004 | Reorganized | $t_1$, $t_2$ | Sankaty | Exit debt financing, controlling |
| 5/13/2003 | Orion Refining | $691.00 | | 6/25/2004 | Liquidated | -- | -- | -- |
| 5/30/2003 | The Penn Traffic Company | $742.00 | | 4/13/2005 | Reorganized | -- | -- | -- |
| 10/8/2003 | Chi-Chi's | $50.00 | | 12/27/2005 | Liquidated | $t_2$ | -- | -- |
| 10/29/2003 | Piccadilly | $159.00 | Yes | 2/13/2004 | Sold to financial buyer | $t_2$ | Yucaipa | Acquirer in 363 sale |
| 1/20/2004 | Wickes | $155.50 | | 12/18/2007 | Liquidated | -- | Sagamore Hill Capital Management, Highland Capital, Contrarian Funds | DIP lender |
| 4/29/2004 | Women First Healthcare | $49.10 | | 12/28/2004 | Liquidated | $t_1$ | Whitney Private Debt Fund | DIP lender |
| 6/14/2004 | ACR Management | $100.00 | Yes | 1/31/2005 | Reorganized | $t_1$, $t_2$ | Carl Marks Strategies | Controlling investor at exit |
| 6/15/2004 | Kiel Bros. Oil Comp. | $50.20 | | 12/29/2006 | Liquidated | -- | -- | -- |
| 11/4/2004 | Rhodes Inc. | $50.00 | | 5/23/2006 | Liquidated | -- | -- | -- |
| 1/11/2005 | Ultimate Electronics | $329.10 | | 1/11/2006 | Sold to strategic buyer | $t_1$ | -- | -- |
| 4/8/2005 | Norstan Apparel | $19.60 | | 8/20/2008 | Liquidated | $t_2$ | -- | -- |
| 7/11/2005 | GT Brands Holding | $208.80 | | 9/6/2006 | Liquidated | -- | -- | -- |
| 1/12/2006 | Musicland | $371.50 | | 1/18/2008 | Liquidated | $t_1$, $t_2$ | -- | -- |
| 1/25/2006 | G+G Retail | $83.60 | Yes | 12/7/2006 | Sold to strategic buyer | $t_1$, $t_2$ | Prentice Capital Management | DIP lender |
| 2/3/2006 | Glazed Investment | $28.60 | Yes | 6/13/2006 | Sold to strategic buyer | -- | -- | -- |
| 12/29/2006 | Advanced Marketing Services | $100.00 | | 11/15/2007 | Liquidated | $t_2$ | Marathon Structured Finance Fund | DIP lender |
| 10/16/2007 | Movie Gallery | $892.00 | Yes | 5/20/2008 | Reorganized | $t_2$ | Sopris Capital Advisors | Exit debt financing, controlling investor at exit |
| 1/22/2008 | Buffets Holdings | $963.00 | | 4/28/2009 | Reorganized | $t_2$ | -- | -- |
| 2/7/2008 | Manchester | $131.60 | | 6/23/2008 | In process | -- | Palm Beach Multi Strategy Fund | Controlling investor at exit |
| 3/26/2008 | Hoop Retail Stores | $100.00 | | 12/15/2008 | Liquidated | $t_1$ | -- | -- |
| 5/2/2008 | Linens 'n Things | $1,740.40 | | 6/15/2009 | Liquidated | $t_1$ | Hilco Consumer Capital/Gordon Brothers Brands | Acquirer in 363 sale |
| 8/20/2008 | Hines Horticulture | $297.40 | | 4/10/2009 | Sold to financial buyer | -- | Black Diamond Capital | Acquirer in 363 sale |
| 10/6/2008 | Paper International | $100.00 | | 6/20/2009 | Reorganized | -- | -- | -- |
| 11/24/2008 | T H Agriculture & Nutrition | $78.00 | | 11/30/2009 | Reorganized | -- | -- | -- |
| 1/5/2009 | Blue Tulip | $6.70 | | 6/5/2009 | Liquidated | $t_1$, $t_2$ | -- | -- |
| 1/5/2009 | Smitty's Building Supply | $21.20 | | 6/29/2009 | Reorganized | -- | -- | -- |
| Finance, insurance, and real estate: | | | | | | | | |
| 10/31/2000 | PRS Insurance Group | | | 3/2/2007 | Liquidated | -- | -- | -- |
| 12/17/2002 | Conseco | $1,794.80 | | 9/10/2003 | Reorganized | $t_1$, $t_2$ | Cerberus Capital, Fortress Investment, JC Flowers, Appaloosa | DIP lender, controlling investor at exit |
| 9/8/2003 | DVI Inc | $1,870.00 | | 11/24/2004 | Liquidated | -- | Ableco Finance (Cerberus) | DIP lender |

**TABLE B.4** – *continued*

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| 3/6/2006 | Plus Funds Group | $7.80 | | 8/2/2007 | Liquidated | $t_1$ | DIP Funding Group, Sphinx Funding Group | DIP lender, exit debt financing |
| 4/13/2006 | USA Commercial Mortgage | $100.00 | | 3/12/2007 | Sold to financial buyer | -- | Compass Partners | Acquirer in 363 sale |
| 12/28/2006 | Ownit Mortgage Solutions | $696.60 | | 1/16/2008 | Liquidated | -- | -- | -- |
| 2/5/2007 | Mortgage Lenders Network | $464.80 | | 6/10/2009 | Liquidated | -- | -- | -- |
| 7/30/2007 | New 118th | $2.70 | | -- | In process | -- | -- | -- |
| 8/6/2007 | American Home Mortgage | $20,553.90 | | 2/12/2009 | Liquidated | $t_1$, $t_2$ | W.L. Ross & Co. | DIP lender |
| 9/28/2007 | NetBank | $87.20 | | 10/3/2008 | Liquidated | -- | -- | -- |
| 2/10/2008 | Cornerstone Ministries Invest. | $159.10 | | 9/25/2009 | Liquidated | $t_1$ | -- | -- |
| 3/31/2009 | USI Senior Holdings | $50.00 | Yes | 6/30/2009 | Reorganized | $t_2$ | -- | -- |

## TABLE B.5
## LINKS BETWEEN CLAIMHOLDERS AND CHAPTER 11 FINANCING AND CONTROL EVENTS

This table reports the frequency in which investors observed holding Chapter 11 claims at the filing of the schedules of assets and liabilities ($t_{1,}$) and the tabulation of votes on the plan of reorganization ($t_2$) also participate in strategic events associated with the Chapter 11 restructuring. The strategic events include providing financing to the bankrupt firm, either as debtor-in-possession (DIP) financing during the case or as new debt and equity financing at bankruptcy exit, and acquiring the firm via a 363 sale. We derive the data on participations in strategic events from public news sources, such as *The Deal Pipeline*, and the debtor's bankruptcy disclosure statement.

| | | Proportion of events including a claimant | |
|---|---|---|---|
| Event: | Total number of events | At filing of Schedule of Assets and Liabilities ($t_1$), all creditors | At votes tabulation ($t_2$), voting creditors only |
| DIP loan | 95 | 58.9% | 34.7% |
| Exit financing (debt) | 37 | 51.4% | 45.9% |
| Exit financing (equity) | 10 | 50.0% | 70.0% |
| Acquirer in 363 Sale | 34 | 11.8% | 2.9% |

## TABLE B.6
## WHAT DETERMINES THAT A CLAIM IS TRADED?

This table presents a set of probit regressions analyzing the likelihood that a given claim is traded. The dependent variable is equal to 1 if the claim was sold and 0 otherwise. The focus is on the size of the claims and, specifically, on the size of trade claims (*Owned by corporation*). Claims are sorted in terciles. Claims in the bottom size-tercile (between $50 and $100 thousand) are considered to be small; claims in the top size-tercile (claims above $300 thousand) are considered to be large. *Mid-size claim* is between $100 and $300 thousand. (Remember that we exclude claims below $50 from the analysis.) Reported coefficients are marginal effects; 0.1 stand for 10% percentage point change in the dependent variable. *Active investors* include asset management firms, hedge funds, and private equity affiliated funds. Omitted category (other creditors) is all claims owned by: custodian banks, potentially financial, insurance, real estate, other financial, government, intra company, and unknown. The institutional type is defined at the parent level. The analysis is at the claim level; i.e., there are multiple claims per bankruptcy. All regressions include industry fixed effects. Standard errors are clustered by bankruptcy. *** , ** and * indicate statistical significance at 1%, 5%, and 10% level, respectively.

| Dependent variable: | 1 if the claim was traded, 0 otherwise | |
|---|---|---|
| Mid-size claim | -0.073* | -0.105** |
| | (0.047) | (0.056) |
| Large claim | -0.044 | -0.079* |
| | (0.042) | (0.053) |
| Owned by: | | |
| Corporations | 0.030*** | -0.054 |
| | (0.013) | (0.038) |
| Banks | 0.241*** | 0.266*** |
| | (0.069) | (0.081) |
| Active investors | 0.271*** | 0.285*** |
| | (0.102) | (0.106) |
| Persons | 0.067 | 0.046 |
| | (0.081) | (0.067) |
| Owned by corporation * Mid-size claim | -- | 0.238** |
| | | (0.160) |
| Owned by corporation * Large claim | -- | 0.197** |
| | | (0.131) |
| Portion of claim that is secured | 0.006 | 0.007 |
| | (0.040) | (0.039) |
| Portion of claim that is unsecured | 0.131*** | 0.128*** |
| | (0.071) | (0.068) |
| Observations | 78,933 | 78,933 |
| Pseudo *R*-squared | 0.10 | 0.12 |

## TABLE B.7

### CREDITOR CONCENTRATION BY INSTITUTIONAL TYPE AND BANKRUPTCY OUTCOME

This table extends the results in Table 2.6 by focusing on the identity of the claimholders by institutional type. Each reported number corresponds to the coefficient in a regression of a bankruptcy outcome on a measure of concentration of interest. *Active investors* include asset management firms, hedge funds, and private equity affiliated funds. The institutional type is defined at the parent level. We include one institutional type at a time (i.e., in Panel A, each number corresponds to a different regression); the correlation in concentration across institutional types is economically and statistically weak. In Panel A, the explanatory variable of interest is the percentage share of the total claims held by a given institutional type. In Panel B, in addition to the share of claims we look at the concentration of the holdings, as measured by Herfindahl-Hirschman index (HHI) *within* an institutional type. The interaction term between the two measures is meant to capture cases where a given institutional type is a large creditor and the holdings are concentrated among a few investors. If for a given bankruptcy an institutional type is missing, HHI is not well defined (i.e., unlike share, it cannot be set to zero); as a result, the number of observations in Panel B varies. In addition to the reported variables, each regression includes benchmark control variables defined in Table 2.6. For compactness of reporting, we omit other control variables and standard errors. Each panel reports two sets of results: (i) creditors' concentration as computed at the file of the Schedule of Assets and Liabilities, and (ii) creditors' concentration as computed at the voting tabulation. Voting tabulation only includes voting (impaired) classes. All models are estimated using linear least squares. ***, ** and * indicate statistical significance at 1%, 5%, and 10% level, respectively.

*Panel A: Explanatory variable –share (%) of the total claims by institutional type*

| | At filing of Schedule of Assets and Liabilities ($t_1$), all creditors | | | | | | At voting tabulation ($t_2$), voting creditors only | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Dependent variables: | Prearranged bankruptcy | Time in bankruptcy | Outcome: Reorganization | Outcome: Sale | Outcome: Liquidation | Recovery rate | Time in bankruptcy | Outcome: Reorganization | Outcome: Sale | Outcome: Liquidation | Recovery rate |
| Banks | 0.32* | -5.37 | 0.21 | 0.06 | -0.23 | -0.38** | -7.48** | 0.24 | 0.05 | -0.25 | -0.28*** |
| Trustees (bonds) | 0.25 | -7.59* | 0.28 | 0.04 | -0.28* | -0.17 | -4.41 | 0.72*** | -0.55** | -0.15 | 0.22 |
| Active investors (all) | 0.23** | -2.30 | 0.15 | 0.11 | -0.19 | -0.01 | 0.10 | 0.40** | -0.23* | -0.13 | -0.17 |
| Asset managers | -0.12 | -0.26 | 0.38* | -0.13 | -0.18 | 0.04 | -0.73 | 0.41* | -0.41*** | 0.03 | -0.13 |
| Hedge funds | 4.63** | -19.75 | 0.76* | 1.32 | -2.04 | -0.30 | 10.74* | 0.83*** | -0.34** | -0.47* | -0.12 |
| PE-affiliated funds | 0.66*** | -4.90*** | -0.32** | 0.49*** | -0.11 | -0.08 | -3.59 | 0.10 | 0.12* | -0.18 | -0.21 |
| Non-financials | -0.36*** | 6.87** | -0.27** | -0.09 | 0.27 | 0.34** | 3.78 | -0.41*** | 0.18 | 0.18* | 0.04 |
| Observations | 119 | 115 | 119 | 119 | 119 | 107 | 108 | 111 | 111 | 111 | 103 |

# TABLE B.7 – *continued*

*Panel B: Explanatory variable –share (%) of the total claims and concentration by institutional type*

| | At filing of Schedule of Assets and Liabilities ($t_1$), all creditors | | | | | | | At voting tabulation ($t_2$), voting creditors only | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Dependent variables: | Obs. | Prearranged bankruptcy | Time in bankruptcy | Outcome: Reorganization | Outcome: Sale | Outcome: Liquidation | Recovery rate | Obs. | Time in bankruptcy | Outcome: Reorganization | Outcome: Sale | Outcome: Liquidation | Recovery rate |
| Banks: | | | | | | | | | | | | | |
| Share | 106 | 0.66 | -20.95** | 0.58 | 0.17 | -0.44 | -0.19 | 80 | -4.83 | -0.21 | 0.14 | 0.21 | -0.59** |
| Concentration | | 0.25 | -3.72 | 0.20 | -0.15 | 0.12 | 0.32 | | -2.88 | -0.27 | 0.08 | 0.23 | -0.36 |
| Share*Concentration | | -0.35 | 18.54 | -0.47 | -0.08 | 0.19 | -0.35 | | -3.11 | 0.54 | 0.02 | -0.69 | 0.68* |
| Trustees (bonds): | | | | | | | | | | | | | |
| Share | 56 | 1.43 | -1.14 | 0.26 | 0.22 | -0.49 | 0.35 | 39 | -15.83** | 0.13 | -0.48* | 0.10 | 0.65 |
| Concentration | | 0.06 | -3.61 | -0.05 | 0.17 | -0.12 | 0.06 | | 0.49 | -0.65 | -0.01 | 0.51 | 0.32 |
| Share*Concentration | | -1.60 | -11.99 | -0.00 | -0.09 | 0.09 | -0.43 | | 25.66 | 0.11 | 0.30 | 0.03 | -0.49 |
| Active investors (all) | | | | | | | | | | | | | |
| Share | 89 | -0.33 | -5.81 | 0.91 | -0.67*** | -0.30 | 0.69 | 86 | -10.32 | 0.57 | -0.82 | 0.49 | -0.62 |
| Concentration | | -0.18 | 1.89 | -0.33** | -0.04 | 0.31 | -0.28 | | -4.20 | -0.46 | -0.06 | 0.59** | -0.28 |
| Share*Concentration | | 0.69 | 1.80 | -0.78 | 0.89*** | 0.07 | -0.81 | | 12.74 | -0.32 | 0.66 | -0.57* | 0.64 |
| Asset managers: | | | | | | | | | | | | | |
| Share | 74 | -0.26 | -3.80 | 0.37 | -0.54 | 0.14 | 1.13 | 70 | -6.09 | 0.15 | -0.90 | 1.04** | -0.79 |
| Concentration | | -0.07 | 0.65 | -0.60*** | 0.00 | 0.63* | -0.27 | | 0.59 | -0.59*** | -0.03 | 0.67** | -0.21 |
| Share*Concentration | | 0.18 | 1.88 | 0.16 | 0.51 | -0.54 | -1.48* | | 11.11 | 0.06 | 0.41 | -0.77* | 0.71 |
| Hedge funds: | | | | | | | | | | | | | |
| Share | 33 | 5.38 | -10.05 | 2.70 | -6.12* | 2.11* | 1.28 | 43 | -33.74 | -1.22 | 2.50 | -1.77 | 2.95 |
| Concentration | | -0.09 | -1.96 | -0.11 | -0.41 | 0.43* | -0.11 | | -4.14 | -0.80*** | 0.19*** | 0.46** | 0.09 |
| Share*Concentration | | 0.80 | -23.94 | -5.22 | 11.55** | -5.12*** | 0.30 | | 46.67 | 1.92 | -2.63 | 1.22 | -2.85 |
| PE-affiliated funds | | | | | | | | | | | | | |
| Share | 35 | 4.03 | -405.89 | -137.67*** | 21.67 | 116.00*** | 47.94*** | 33 | -179.05*** | 5.89 | -5.56 | -0.33 | -5.47*** |
| Concentration | | 0.47* | -18.15 | 0.17 | 0.82 | -0.99** | 0.65*** | | -17.15 | 0.40 | -0.32 | -0.08 | -0.79** |
| Share*Concentration | | -3.16 | 402.51 | 137.26*** | -21.07 | -116.20*** | -47.96*** | | 165.56** | -6.21* | 5.81 | 0.40 | 5.46*** |
| Non-financials | | | | | | | | | | | | | |
| Share | 117 | -0.42** | 6.29 | -0.48* | 0.08 | 0.33 | 0.70* | 108 | 4.67 | -0.68** | 0.12 | 0.50* | 0.50 |
| Concentration | | -0.13 | -4.06 | -0.33 | 0.54 | -0.19 | 0.34 | | -4.63 | -0.49 | 0.15 | 0.34* | 0.11 |
| Share*Concentration | | 0.45 | -3.13 | 0.86 | -0.70 | -0.28 | -1.36 | | -2.31 | 0.57 | 0.21 | -0.80 | -1.09** |

## TABLE B.8
## ROBUSTNESS: IMPACT OF INDUSTRY FIXED EFFECTS

This table displays how the results in Table 2.5 would be affected by the exclusion of the industry fixed effects. In Panel A, we display the coefficient on *Creditor concentration ($t_1$)* both with and without industry fixed effects. In Panel B, we display how the exclusion of industry fixed effects impacts the overall *R*-squared of the regressions. Note that the *R*-squared reported in Table 2.5 (and other tables in the paper) is the *within* industry *R*-squared, while the values reported in Panel B of this table are overall *R*-squared.

*Panel A: Coefficient on Creditor concentration ($t_1$)*

| Dependent variable | With industry fixed effects | Without industry fixed effects |
|---|---|---|
| Prearranged bankruptcy | 0.371*** | 0.351** |
| | (0.089) | (0.095) |
| Time in bankruptcy | -6.671** | -7.439** |
| | (2.24) | (2.496) |
| Reorganized | 0.389** | 0.485** |
| | (0.135) | (0.140) |
| Sold | 0.073 | 0.065 |
| | (0.297) | (0.253) |
| Liquidated | -0.465 | -0.555 |
| | (0.353) | (0.332) |
| Recovery rate | -1.096 | -0.884 |
| | (0.616) | (0.585) |

*Panel B: R-squared*

| Dependent variable: | With industry fixed effects | Without industry fixed effects |
|---|---|---|
| Prearranged bankruptcy | 0.123 | 0.066 |
| Time in bankruptcy | 0.396 | 0.377 |
| Reorganized | 0.316 | 0.244 |
| Sold | 0.171 | 0.127 |
| Liquidated | 0.293 | 0.196 |
| Recovery rate | 0.188 | 0.138 |

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